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Essays on Subprime Lending, Present Bias, and Risk Salience

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Essays on Subprime Lending, Present Bias, and Risk Salience

by

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Essays on Subprime Lending, Present Bias, and Risk Salience

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In chapter 1, I examine the consequences of a policy change in Rhode Island that lowered the cap on payday loan fees (interest rates) from 15% of the principal to 10%. I use a difference-in-difference framework and a unique proprietary dataset of payday loan transactions to estimate the impact on market outcomes. I find that the lenders always charge the prevailing cap, creating a strong first stage. I also find that demand for payday loans increases both at the extensive and intensive margins. I show that debt cycles become longer and more likely to end with default. Moreover, I find that no lenders exit the market after the policy change, implying that they had substantial market power. The increase in affordability of the loans increases consumer surplus by about 44%. Many consumer rights advocates believe that subprime consumers tend to be time-inconsistent. With this assumption, welfare implications of a fee cap are not straightforward, because the gain from higher affordability can be dominated by the loss from amplified time-inconsistent behavior. To address this issue, in chapter 2 I develop a dynamic model of payday loan usage with naïve hyperbolic discounting. I calibrate the model in such a way that the simulated means are as close as possible to empirical means for Rhode Island under both regulation regimes (10% and 15% fees). Using simulations of the model, I show that a tighter fee cap is welfare-improving for all consumers, regardless of their degree of time-inconsistency. Furthermore, I find that a ban is more beneficial than a fee cap to highly time-inconsistent consumers but harms time-consistent consumers. In chapter 3, I examine whether earthquake risk salience increases in an area in response to the news of earthquakes in other parts of the world. Using 20 years of housing and earthquake data, I show that disastrous earthquakes happening in other parts of the world decrease home prices in high-risk zip codes relative to low-risk zip codes. Moreover, I find that higher casualties are associated with higher price effects. I also show that the price effects decay after one month.

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Chapter 1

Consequences of Payday Loan Regulation: Evidence from Rhode Island

1.1 Introduction

Payday loans attract substantial attention from the media and legislators who criticize the payday-lending companies, mainly for charging high fees,[1] and trapping borrowers in "debt cycles."[2] Consumer Financial Protection Bureau (CFPB, 2016) reports that in 2015 there were more payday loan stores in the US than McDonald's restaurants.[3] An article by The New Yorker mentions that the payday loan market accounts for nearly $40 billion dollars annually, and serves more than nineteen million households a year (Taylor, 2016). When a consumer takes out a payday loan, she has to repay it in one "balloon" payment, which is usually a large portion of her income. When the due date arrives, she can pay just the fee, and roll the loan over for another pay period. When a loan is rolled over several times, it is said that the borrower is trapped in a debt cycle. This, combined with the high fees, results in the borrower paying a large sum in interest. For instance, if a person gets a bi-weekly $400 loan at a 15% fee, and rolls

[1]In the payday loan market, the interest and all other costs that the borrower has to pay on top of the principal are referred to as fees.

[2]For a list of other criticisms of payday loans, see Montezemolo (2013).

[3]According to the report, the bureau estimates that there were 15,766 payday loan stores in the US in 2015, compared to 14,350 McDonald's fast food outlets in 2014.

the initial loan over for 7 periods, she would pay $0.15 \times \$400 \times 8 = \$480$ (or 120% of the principal) in fees, during only 4 months. Therefore, there is concern that "the cost of the loans turn temporary financial shortfalls into long-term crises." (Bush, 2014)

To address the concerns with payday loans, many states have put regulations in place, the most popular form of which are fee caps. Twenty six states have fee caps that maintained the market, while seventeen others, plus the District of Columbia, outright ban the loans, or impose fee caps that are effectively a prohibition, as they have pushed all storefront lenders out of their respective markets.[4] In this paper, I investigate a regulation in Rhode Island that lowered the cap on payday loan fees from 15% of the principal to 10%. Policy changes similar to this were, and continue to be, considered by other states and the federal government. For example, in April 2016, the Alabama Senate approved a payday loan reform bill that would decrease the fee cap from 17% to 5% (Lyman, 2016). Comparably, the US Congress introduced a new legislation to cap payday loan fees in 2014, which did not pass (Layton, 2014). Therefore, it is essential to understand how such policies impact consumers and their welfare.

In this paper, using a unique proprietary data-set of payday loans and a difference-in-difference framework, I study a policy change in Rhode Island that lowered the fees on payday loans from 15% to 10%, or equivalently, brought the APR from approximately 390% down to 260%. The reduced-form results indicate a strong first stage, with the lenders always charging the prevailing cap. This sharp price drop can be easily observed in a raw plot of the administrative data. I find the borrowers are price-sensitive both at the extensive and intensive margin, as indicated by a 10% increase in the number of borrowers, a 5% increase in the number of loans per borrower, and a 5% increase in average principal. These changes combined, point to a 20% increase in borrowing as a result of lowering the fees. I show that this impact unfolds immediately and persists over time. These results are robust to the inclusion of macro-level controls, different specifications, choice of control group, and placebo tests.

Moreover, I show that no stores close after the new policy, suggesting that market power exists in this market, and also implying that the quantity shifts trace out the demand curve. [5] I also show that default at the individual loan level occurs less often, possibly because the policy change makes defaults

[4]Prohibitive caps are frequently in the form of a 36% APR ceiling.

[5]Another assumption needed for this to be true is that the marginal cost of lenders has a lower level than the fee caps. I argue later in section 6 that this assumption is reasonable.

relatively more expensive than rolling over or paying off a loan. Additionally, I find that lowering the fees causes loan sequences to become 25% longer and 2.4 percentage points more likely to end with default. Finally, I find that lower fees do not attract a fundamentally different group of borrowers to the market, as indicated by only negligible changes in average income and average age of borrowers.

The economic literature on payday loans primarily revolves around papers that study the impact of restricting access to payday loans on outcomes that are indicative of financial well-being, with mixed results. Some papers find adverse effects such as increase in Chapter 13 bankruptcy (Skiba and Tobacman, 2009), decrease in paying mortgage, rent and utility bills (Melzer, 2011), and decrease in job readiness among military personnel (Carrell and Zinman, 2014). Others observe favorable effects such as easier recovery from natural disasters (Morse, 2011), or decrease in bounced checks (Morgan, Strain, and Seblani, 2012). A related paper is Zinman (2010) which investigates the effect of a similar policy change in Oregon, and finds a negative effect of restricting the market on employment and subjective (self-reported) financial condition.

My paper is the first economic study of payday loan fee caps in which no attrition in the supply side ensued from the policy. This is an important distinction because it allows estimation of demand and consumer surplus. My study is also the first analysis in this market that uses large-scale administrative data on payday borrowing, instead of survey data or small administrative data (for a single lender). Furthermore, it is the first academic paper that explicitly takes into account the loan sequence phenomenon, the main channel through which borrowers incur high interest costs. Finally, this paper provides the first estimates for price-elasticity of demand for payday loans.

Having the reduced-form results at hand, I examine how consumer welfare is affected. Price ceilings are often seen as a way of increasing efficiency when market power is present. In the case of interest rates, caps can also be viewed as a transfer from lenders, who have low marginal utility, to borrowers, who have high marginal utility, and therefore act as a primitive means of social insurance (Glaeser and Scheinkman, 1998). They also protect small and inexperienced borrowers against exploitation (Blitz and Long, 1965).

If consumers are rational, lower prices almost certainly make consumers better off. I argue below that the change in fee cap, accompanied with no lender exits and low marginal cost, identifies two points on the demand curve. Using that demand curve, the change in consumer surplus is calculated to be about

+2.6 million dollars annually, or a 44% increase (assuming a linear demand function). Furthermore, if we assume that loan losses (cost of default) are the major contributor to the marginal cost of lenders, the change in producer surplus is estimated to be about -1.6 million dollars annually, or a 26% decrease. Market efficiency (total surplus) increases by about 10%. The estimated demand and the estimated marginal cost imply an unconstrained equilibrium fee of about 21%, which is strictly consistent with what is actually charged by the same lenders in states with no fee caps.[6] This suggests that the demand and marginal cost functions used in the analysis are reasonable.

These findings are important to understand demand and supply in the payday loan market, and to make informed regulatory decisions accordingly.

The rest of the paper is structured as follows: In section 2, I introduce the payday loan market and borrowing patterns in detail. In section 3, I describe the data and provide summary statistics. In section 4, the research design is laid out. In section 5, the reduced form results are presented. Section 6 contains the analysis of demand and consumer surplus. Section 7 concludes.

1.2 Background

Payday loans evolved from what used to be called "wage buying" in the late 19th century United States. To get a payday loan, the borrower walks into a payday loan store and receives cash in return for a post-dated check in the amount of the loan plus fees, dated on the borrower's next payday.[7] The loan should be repaid in only one payment, with no amortization. The duration of the loan depends on how frequently the borrower receives her paycheck and therefore can range from a few days to a month.[8] If the borrower does not return on her payday to repay the loan in cash and if the lender is unable to cash the check (because of non-sufficient funds, a closed account, etc.) default occurs.

Payday loans usually have a principal between \$100 and \$500. They are easy to get in terms of location, requirements, and time. The stores often establish themselves in places that are close to the impoverished, minorities, and military personnel (Gallmeyer and Roberts, 2009). The application process

[6] For example, in Delaware, a state similar to Rhode Island in terms of region, size, and population, but with no fee cap, the lenders charge 20% fees.

[7] The check is a back-up collection method. Lenders require in-person cash repayment in most cases.

[8] Many states have placed a minimum on the duration of the loans. In Rhode Island, the minimum is 13 days.

is quick and easy. An identification document and proof of income are often the only required paperwork. Some lenders do not perform any credit checks, and the ones that do, query subprime credit bureaus[9] and have lenient approval thresholds. According to a lender's website, the application process requires only 10-15 minutes.[10]

The interest and all other costs that the borrower has to pay on top of the principal are referred to as "fees." These fees depend only on the amount of the loan and are independent of the duration of the loan or the borrower's history. The fees range from 10% to 25% of the principal, with a national median around 15%. These fees translate into triple-digit APRs. For instance, a two-week loan with a 15% fee has an APR of 390% (15% $\times$ 26 bi-weeks). The lenders argue that these loans are designed to satisfy a one-time short-term emergency need for cash (such as car repair, medical expenses, etc.), and APRs (which are year-round) are an inappropriate measure of their expensiveness. Consumer advocates respond that since the loans are often rolled over several times, the borrowers actually incur the costs of high interest.

Although payday loans are designed to be repaid in one payment, if the borrower is unable to do so when the loan is due, she can rollover the loan over for another pay period, paying just the fee. To rollover a loan, the borrower does not need to write a new check, unless the previous one is going stale. "Quick New Loans" involve a similar procedure. A quick new loan is when the borrower repays a loan, but takes out a new one before receiving his/her next paycheck (For instance, when a borrower who gets paid bi-weekly gets a new loan in less than 14 days after repaying the previous one). Using these two concepts, I define a loan sequence as an initial loan plus the series of subsequent rolled-over or quick new loans. A sequence ends with either repayment (and no new loans for at least one pay period) or default. I show below that in my data about 30% of the sequences consist of only one loan, meaning that the borrower was able to repay the loan the first time it was due, and stay out of the market for at least one pay period. On the other hand, 25% of the sequences include at least 10 loans. policymakers refer to such sequences as debt cycles and consider them harmful to the financial well-being of the households who are subject to them.

Overdraft protection (or courtesy pay) is believed to be the closest substitute

[9] These credit bureaus are different from prime credit bureaus such as Experian or Transunion, and the credit scores that they generate focus on borrowing histories in the subprime market.

[10] https://www.advanceamerica.net/questions

for a payday loan, because it does not require a collateral or a durable purchase (Zinman, 2010). For each overdraft (even in small amounts) from the bank account, a fixed fee is charged by the bank. Currently, these fees average around $30 per overdraft and are not subject to any price or usage regulations.

1.3 Data

I use a unique proprietary dataset held by a subprime credit bureau that contains transaction level information on all loans issued by several major storefront lenders from the beginning of 2009 to the end of 2013. The dataset contains about 100 million loans (including rollovers) to about 5 million unique borrowers in 36 states. For each transaction record, I observe lender information (lender identifier, and store zip-code), borrower information (borrower identifier, age, and monthly income), and loan terms (principal, fee, start date, due date, date paid, and default indicator).[11]

The Rhode Island subset includes 742,602 loans and 23,576 unique borrowers. To put these numbers into perspective, Rhode Island had a population of about 1 million people living in 400,000 households during the study. According to a report by Experian in 2012, approximately 20% of Rhode Island residents were subprime consumers,[12] while the national average is 23%. The loans are issued by monoline lenders with a total of 25 stores within the state. An inquiry to the Rhode Island Department of Business Regulation revealed that there were a total of 33 licensed payday loan stores in Rhode Island between 2009 and 2013.[13] Assuming that each store gets the same share of the market, the dataset covers over 75% of the store-front payday loan transactions in Rhode Island. The location of all payday loan stores operating in Rhode Island between 2009 and 2013 is depicted in Figure 1.1a. Figure 1.1b depicts population densities in Rhode Island. These two figures demonstrate that the stores are located in the more densely populated areas of the state.

Table 1.1 shows summary statistics for the variables of interest in the Rhode Island subset. The age of borrowers is distributed rather symmetrically, around a median of 40 years. The median annual income of borrowers is about $22,600, which slightly exceeds Rhode Island's official poverty line for a family of four in

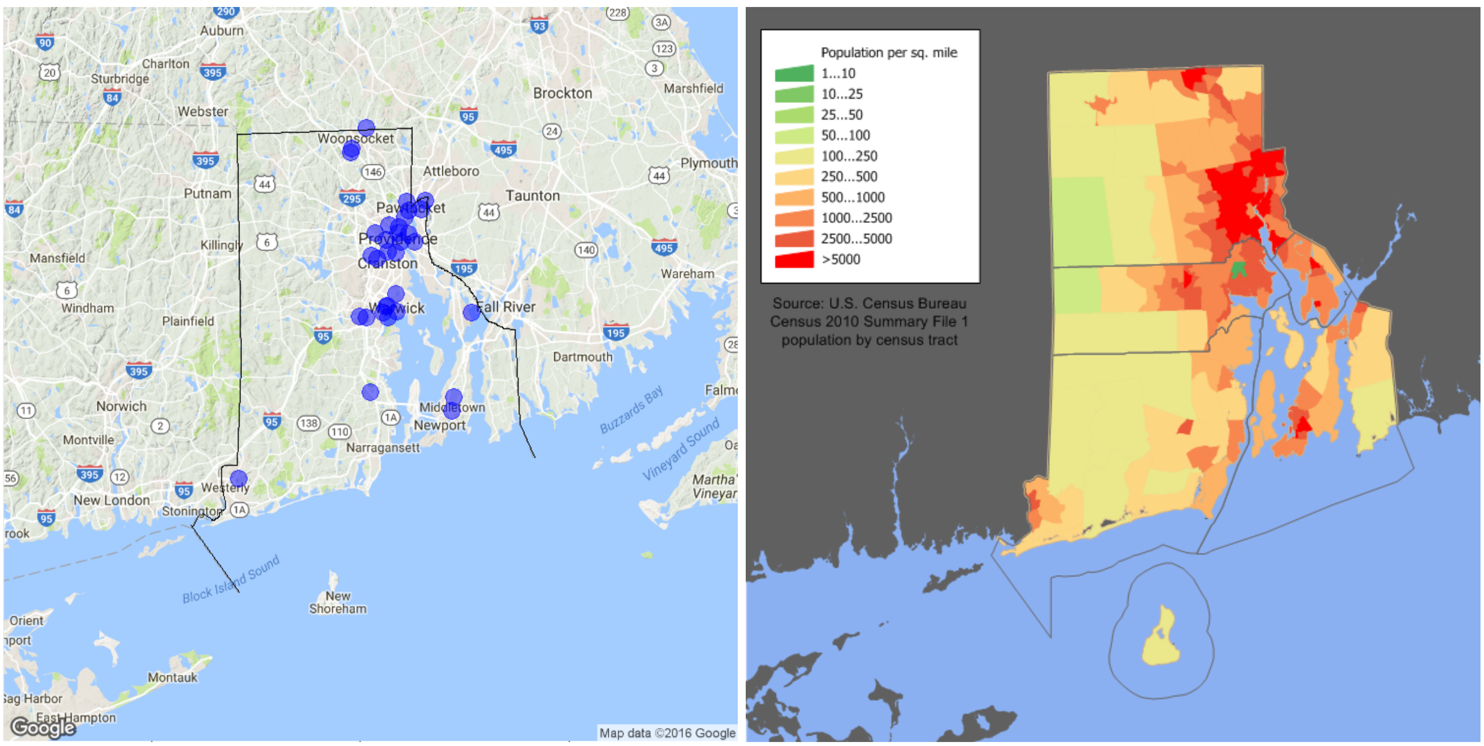
[11]The dataset does not identify borrowers or lenders.

[12]Subprime consumers are classified as having an Experian VantageScore below 600.

[13]Earlier, I quoted a report from CFPB that there are more payday loan stores in the US than McDonald's restaurants. Based on an online search, there are 32 active McDonald's outlets in Rhode Island as of October 2016.

Figure 1.1: Distribution of Payday Loan Stores and Population within Rhode Island

(a) Location of Payday Loan Stores (b) Population Density



The blue circles indicate all the 33 payday loan stores that operated in Rhode Island between 2009 and 2013. No stores close during this timeframe, and only two stores enter (which are shown here, but are not included in the sample). The right graph shows the distribution of population in Rhode Island, with the more densely populated areas colored in darker shades of red. Comparing the two graphs shows that the stores are located in areas of the state where the population is more concentrated.

2010 (\$22,000). Even after assuming that the borrower is not the sole breadwinner in the household and another household member brings in the same amount of money, the median payday loan user still makes less than the state median household income of \$56,000 in 2010. This supports anecdotal evidence that payday loan users are predominantly low-income.

As mentioned before, loan sequences are a key feature of this market, from a policy-making point of view. I apply the definition of a loan sequence to the entire sample of Rhode Island loans, and obtain 81,189 sequences. The three quartiles for the number of loans per sequence are 1, 3, and 10. I define the duration of a sequence as the number of days between the first loan's initiation and the last loan's due date. Since borrowers have different pay frequencies, sequences with the same number of loans can have different durations. The three quartiles for duration are 23, 60, and 174 days. Loan sequences can be extremely long. The top 1% of the sample contain 69 or more loans, and last for almost 4 years. The cost of borrowing in this market is sum of the fees paid over the duration of the sequence (abstracting away from discount rates and opportunity costs that are negligible in short periods). This cost is zero when the borrower defaults after just one loan, paying no fees for the sequence. The variable "Total Fees per \$100 in Sequence" measures this cost, and has a mean of \$95, suggesting that, on average, the consumers pay \$95 in fees for each \$100 that they borrow. Sequences which begin in the first period might be continuations of sequences beginning before the first period. Similarly, sequences ending in the final period might have continued after the final sample period. Therefore, the numbers reported here (for number of loans per sequence, duration of sequences, and total fees per \$100 in sequence) underestimate the actual values.

Borrowers are not contractually barred from decreasing the principal with each rollover, but in practice, they generally do not use this informal amortization mechanism. For about 83% of the sequences with at least two loans in the sample, the last loan in the sequence has equal or higher principal than the first, confirming the lack of amortization in this market (also documented by Burke, Lanning, Leary, and Wang (2014)). Lack of amortization goes hand in hand with the rollover behavior because the borrower must either allocate a large portion of her income to repay the loan, or less painfully, pay the fee and roll the loan over. Payment-to-income ratio shows the portion of a borrower's paycheck that should go toward repaying a payday loan. Since consumers who are paid more frequently (e.g., weekly) receive less money with each paycheck, this ratio is larger for them. The average and median are about 50%, which

Table 1.1: Summary Statistics for Rhode Island Payday Loans, 2009-2013

Variable	Mean	Std. Dev.	1st Pct	Q1	Median	Q3	99th Pct
Age (Years)	41.01	13.54	19.25	29.90	41.01	50.71	74.89
Monthly Income ($)	2222	1320.65	468	1196	1887	2838	6684
Pay Frequency	Weekly: 41%, Biweekly/Semimonthly: 39%, Monthly: 20%						
Principal ($)	380.2	93.95	100	320	435	450	450
Days until Due	17.97	6.49	13	14	14	20	35
Loans per Borrower	31.55	38.52	1	4	16	45	177
Loans per Sequence	8.72	13.78	1	1	3	10	69
Length of Sequence (Days)	158	257.33	13	23	60	174	1385
Total Fees per $100 in Seq.	95	152	0	15	40	109	740
Last Loan in Seq.$\geq$ First Loan in Seq.	82.7%						
Payment-to-Income Ratio	0.52	0.29	.10	0.30	0.46	0.68	1.42
Default (Individual Loans)	1.89%						
Default (Sequences)	17.31%						
Quarterly Personal Income ($million)	46.40	2.11	42.87	44.72	46.80	48.37	49.31
Monthly Unemployment Rate (%)	10.58	0.92	9	10.07	10.70	11.20	12

The data include about 750,000 loans issued by 2 lenders with 25 stores in Rhode Island, and taken out by 23,000 unique borrowers, from the beginning of 2009 to the end of 2013. The statistics for Quarterly Personal Income and Monthly Unemployment Rate are also for Rhode Island during the same timeframe, and are obtained from BEA and BLS, respectively.

demonstrate how difficult it is for a typical borrower to pay back their loan in one payment.

About 2% of the individual loans in the sample are reported by the lenders as defaulted. For comparison, according to S&P/Experian Consumer Credit Default Indices, the default rates were 2.83% for bank cards and 1.03% for auto loans in February 2014. However, if we consider loan sequences instead, about 17% end in default. From a lender's point of view, the default rate of individual loans is more relevant because before each rollover, the lender receives the fee for the current loan. Therefore each rolled-over loan is as profitable as a new loan issued to a new borrower.

In addition to the described dataset, I use state-level quarterly personal income data from the Bureau of Economic Analysis (BEA), and state-level monthly unemployment rate data from the Bureau of Labor Statistics (BLS). These variables control for macroeconomic trends that could affect payday loan usage in Rhode Island, beyond the change in fees.

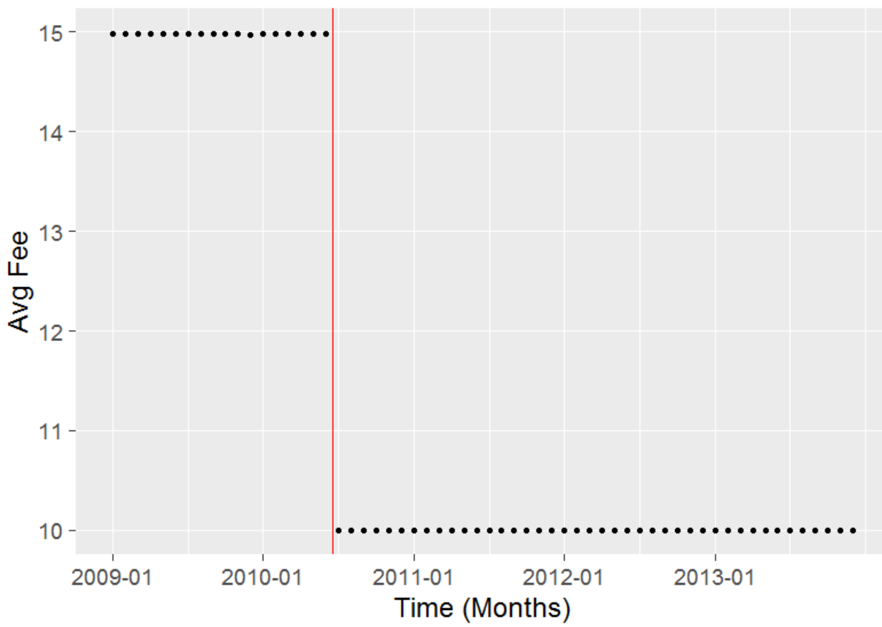
1.4 Research Design

From 2005 to June 2010, Rhode Island law relating to financial institutions (RI Gen L § 19-14.4) restricted payday loan licensees to the following practices:

- No licensee shall charge deferred deposit transaction fees in excess of fifteen percent (15%) of the amount of funds advanced.
- The maximum amount of a single customer's check (principal + fees) is five hundred dollars ($500).
- The maximum aggregate amount of concurrently outstanding checks held by the licensee or its affiliate from the same customer is five hundred dollars ($500).
- The maximum number of concurrently outstanding checks held by the licensee or its affiliates from the same customer is three (3).
- The maximum number of rollovers permitted is one.

In February 2010 a new bill was introduced in the Rhode Island House of Representatives that lowered the cap on advanced fund fees from 15% to 10%, without altering the other restrictions. This bill was enacted on June 25, 2010, and effective on July 1st. Hereafter, I refer to this updated law as the New Regulation,

Figure 1.2: First Stage



Each point represents the average fees charged by the lenders at each month. The lenders always charge exactly 15% before the New Regulation, and 10% right after it.

or NR. As depicted in Figure 1.2, the lenders perfectly complied with the new regulation (they always charged 15% fees before NR, and 10% right after it), and hence, a strong first stage exists.

$$\log(Y_{st}) = \alpha_0 + \mu_s + \phi_{\mathrm{y}(t)} + \gamma_{\mathrm{m}(t)} + \lambda_s t + \beta \boldsymbol{X}_{st} + \delta \,\mathrm{POST}(t) + \Delta \,\mathrm{POST}(t)\,\mathrm{RI}(s) + \epsilon_{st} \tag{1.1}$$

In this equation, the level of observation is state (s) at month (t). Five years of data are available, so t ranges from 1 to 60, and $\mathrm{y}(t)$, $\mathrm{q}(t)$ and $\mathrm{m}(t)$ represent the year, quarter and month associated with each t. Since different states have different market scales, I use log transformation and include state fixed effects to make the changes comparable. In addition to controlling for monthly and yearly fixed effects, I use a separate linear time trend for each state. In the next section, I show that the results are not sensitive to alternative time specifications, such as year-month fixed effects (i.e., having a fixed effect for January 2009, instead of one fixed effect for year 2009 and one for the month of January), or state-month fixed effects (i.e., seasonal trends that vary by state). Furthermore, I control for state-level macroeconomic variables ($\boldsymbol{X}_{st}$) that could affect the demand for payday loans. Following Morse (2011), $\boldsymbol{X}_{st}$ includes quarterly personal income ($\mathrm{PI}_{s,\mathrm{q}(t)}$) (from BEA) and monthly unemployment rates ($\mathrm{UR}_{s,\mathrm{m}(t)}$) (from BLS) for each state. $\mathrm{POST}(t)$ and $\mathrm{RI}(s)$ are, respectively, indicator functions for whether the observation is post-NR (July 2010 and after, $t \geq 19$), and for whether the state is Rhode Island. Since the treatment starts in mid-2010, the year fixed effects do not perfectly align with $\mathrm{POST}(t)$ in equation (1.1). The difference-in-difference parameter (Δ) captures the causal effect of NR on Y_{st}.

As in any difference-in-difference analysis, it is imperative to choose appropriate control groups. Aside from Rhode Island, loans from 35 other states are available in the data-set. Out of these 35 states, 6 are available only partially (1, 6, 20, 23, 37 and 39 months). Since the observations for these states fall entirely or mostly on one side of the pre- or post- periods, I exclude them from the analysis. From the remaining 29 states, I remove 11 states which went through a policy change between 2009 and 2013 that could affect supply or demand for payday loans.[14][15] From this point on, I refer to these 18 states as CG18.

To make the control group more homogeneous, I remove from CG18 all states with no price cap (Idaho, Missouri, Nevada, South Dakota, Utah), or with high caps that are barely binding (Louisiana, North Dakota, Texas, Wyoming)[16]. This reduces the control group to Alabama, California, Florida, Indiana, Iowa, Kansas, Michigan, Nebraska and Oklahoma, that I refer to as CG9. These states either have a fee cap between 10% and 15% (of the principal or of the check), or a step pricing scheme that starts with 15% for the first \$100, and goes down a bit for the extra \$100 increments of the principal.

Figure 1.3 depicts the evolution of variables of interest in Rhode Island in contrast to CG9. While Rhode Island experiences a sharp drop in average fees, the average fees stay almost flat for CG9 states. The number of borrowers, average principal, and total loan value (sum of principals) in Rhode Island show a striking divergence from the states in CG9 after NR. The number of loans per person and default rate are highly volatile and do not display changes as

[14] A list of payday lending legislations are made available by the National Conference of State Legislatures at www.ncsl.org.

[15] None of these regulations are in the form of a clear-cut change in fee caps that can be used with Rhode Island in the analysis.

[16] Lenders charge 18.5-22% in states with no fee caps. The effective cap in these four states are in the same range.

evident as the other variables mentioned.

It is important to note that the jump in average principal (and total loan value) is partly a mechanical result of the law, rather than an economic response to the lower fees (which is what I intend to study in this paper). The law restricts the maximum amount of a customer's check, which is principal plus fees, to \$500. Therefore, when the fee is brought down, the lender can lend up to a slightly higher amount. In practice, the principals do not exceed \$435 when the fee is 15%, and \$450 when the fee is 10%. Before NR, 43% of loans were at the maximum amount, but this number rose to 55% when fees went down. To capture only the portion of the change in principal that results from borrowers' response to lower fees, I assume that every borrower in the pre-NR period who got a \$435 loan, would have taken out \$450 if they could. With this conservative adjustment,[17] the increase in average principal (and consequently, total principal) shrinks, but remains noticeable. Figure 1.4 compares average principal before and after the adjustment. In the rest of the paper, I use the adjusted version of average principal and total loan value.

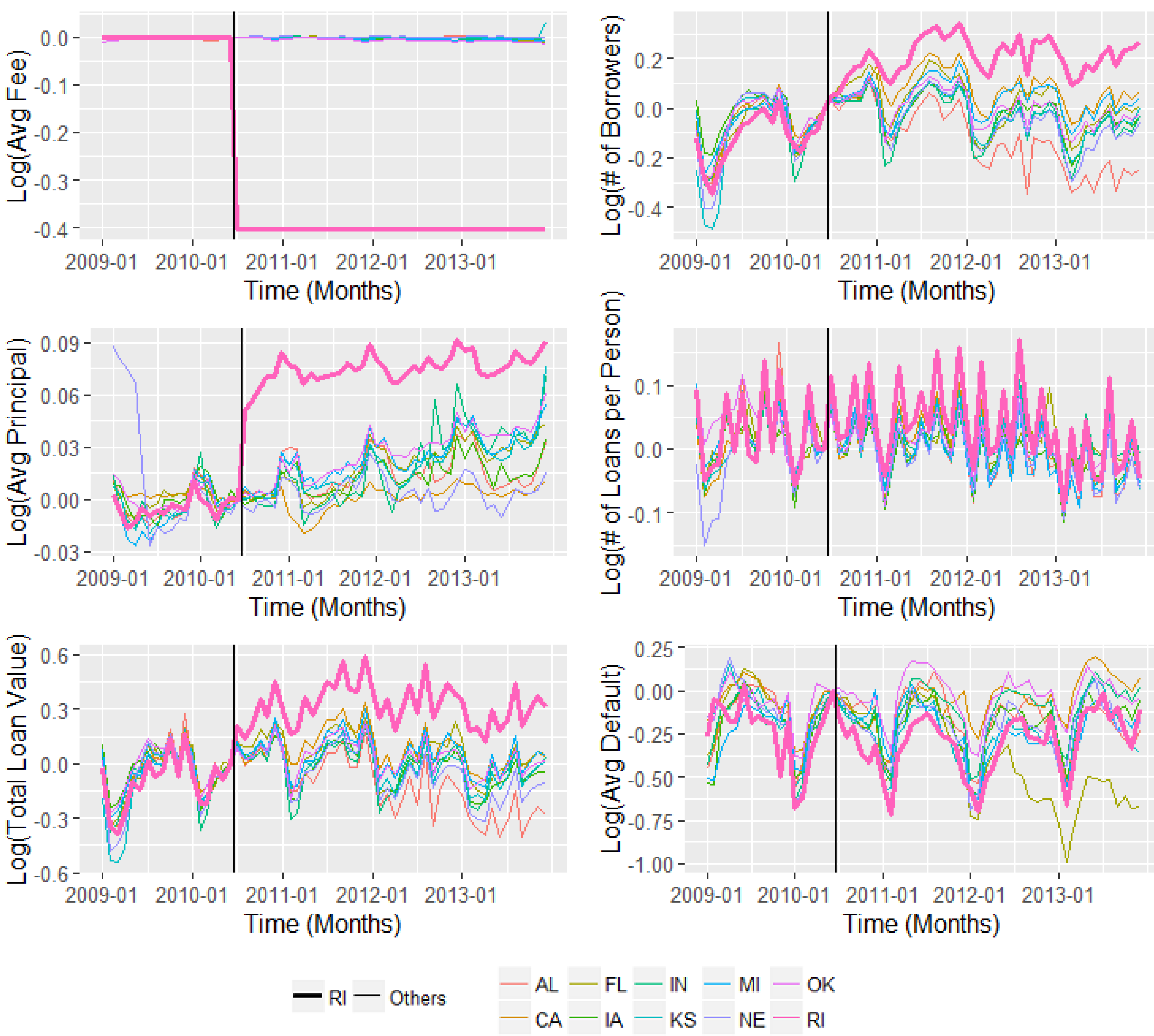
In the next section, I estimate the change in several market outcomes using the explained research design. Since CG9 includes states which have similar regulation environments to that of Rhode Island, I consider it the main control group; However, I show that the significance and magnitude of the results do not depend on the choice of the control group, although the estimates become less precise with CG18.

1.5 Reduced Form Results

Estimation results for different outcomes of interest are presented in Tables 1.2-1.5. As can be seen in the table, the results are not sensitive to the inclusion of macro-level control variables, the choice of control group, or how seasonality and time trends are controlled for. The standard errors are clustered at the state level. Since the number of clusters are small (< 50), to determine statistical significance I follow Cameron and Miller (2015) in using student-t distribution with $G - L$ degrees of freedom, in which G is equal to the number of clusters (states), and L is the number of cluster invariant variables. In case of equation (1.1), in each cluster the constant and state identifier are invariant, hence $L = 2$. This results in larger critical values compared to those obtained by assuming

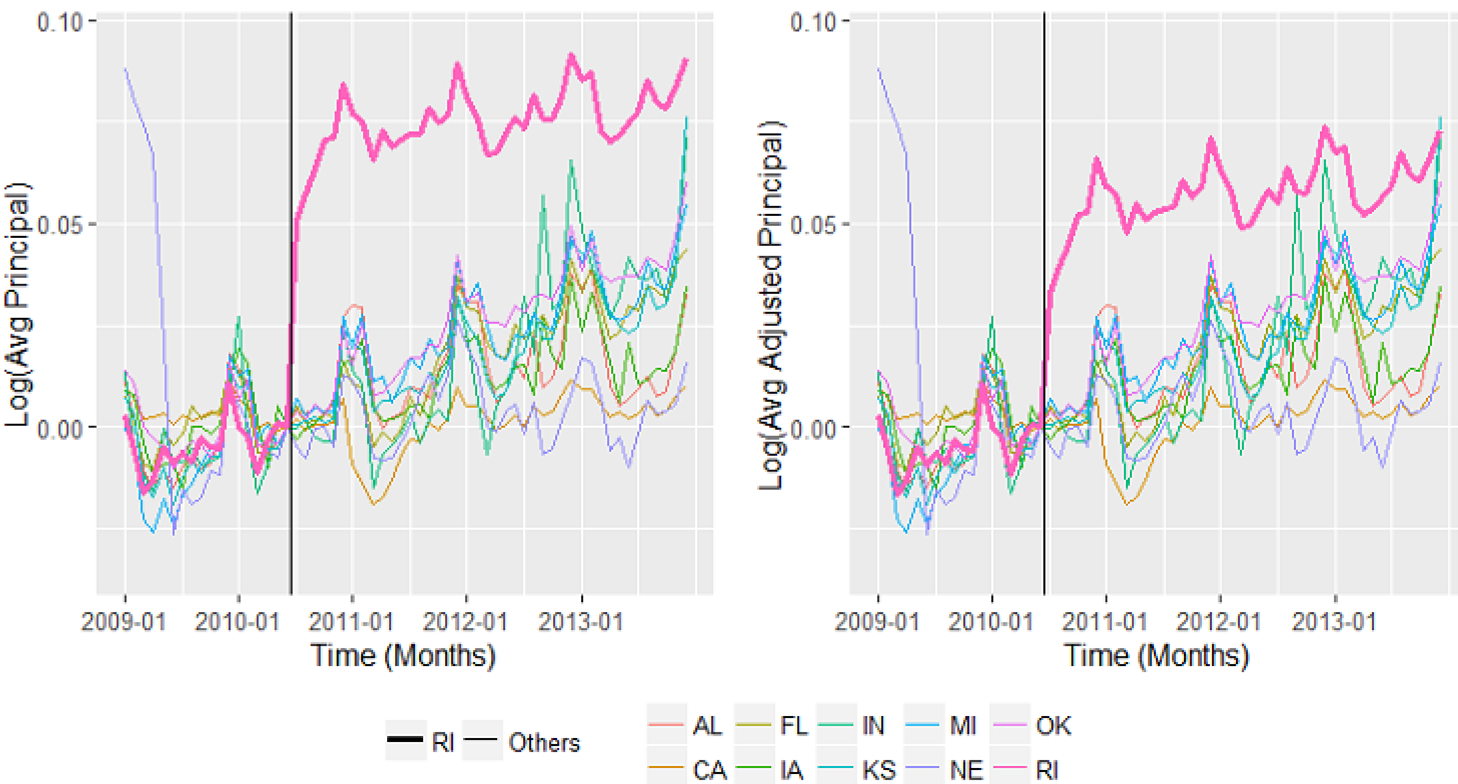
[17] Here "conservative" is meant that the borrowers could have chosen any amount between \$435 and \$450, and adjusting to \$450 leads to an underestimation of sensitivity to lower fees.

Figure 1.3: Evolution of Different Variables in Rhode Island Vs. CG9



These graphs show how the variables of interest evolve differently in RI compared to the states in CG9 control group, after NR. CG9 includes states which have similar payday loan regulations to that of Rhode Island, and which don't go through any regulatory changes between 2009 and 2013. In all graphs, the values for each state are log-transformed and subtracted from the value in June 2010, so that all states have the same origin before NR. The number of borrowers, average principal, and total loan value show strikingly different behavior in RI compared to the other states. Other variables are very volatile.

Figure 1.4: Average Principal with and without Adjustment



The left graph shows the change in average principal without adjustment, and the right graph shows the change with adjustment. The adjustment takes into consideration that the maximum possible principal increased mechanically after the fees went down, so that only the part of the change that is an economic response to the lower fees remains. After the adjustment, the rise in average principal shrinks, but remains noticeable.

Table 1.2: Regression Results for Number of Borrowers and Number of Loans per Borrower

Dependent Variable (log)	*Number of Distinct Borrowers*					*Number of Loans per Borrower*				
Specification	(I)	(II)	(III)	(IV)	(IV)	(I)	(II)	(III)	(IV)	(IV)
Control Group	CG9	CG9	CG9	CG9	CG18	CG9	CG9	CG9	CG9	CG18
Baseline Value for RI	~ 5800 Individuals per Month					~ 1.8 Loans per Month				
POST x RI	**0.121 *****	**0.100 *****	**0.117 *****	**0.100 *****	**0.115 *****	**0.049 *****	**0.046 *****	**0.048 *****	**0.046 *****	**0.055 *****
	(0.01)	(0.008)	(0.009)	(0.011)	(0.031)	(0.005)	(0.006)	(0.006)	(0.006)	(0.01)
Personal Income	-	Y	Y	Y	Y	-	Y	Y	Y	Y
Unemployment Rate	-	Y	Y	Y	Y	-	Y	Y	Y	Y
State F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	-	Y	Y	Y	Y	-	Y	Y
Month F.E.	Y	Y	-	-	-	Y	Y	-	-	-
Month x State F.E.	-	-	-	Y	Y	-	-	-	Y	Y
Year x Month F.E.	-	-	Y	-	-	-	-	Y	-	-
State x Linear Trend	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R squared	99.8%	99.8%	99.9%	99.8%	99.7%	92.5%	92.5%	97.8%	91.3%	89.3%
Observations	600	600	600	600	1140	600	600	600	600	1140

Significance levels: *** (1%), ** (5%), * (10%)
Standard errors clustered at the state level.
Critical values are based on T(G - L) distribution (Cameron and Miller, 2013).

a normal distribution. For instance, when using CG9 as the control group, significance at the 95% level is determined by the t-statistic being larger than 2.36, instead of the usual 1.98.

The results show that lower fees lead to more people taking out loans (an increase of about 10% in the number of borrowers), more frequently (an increase of about 5% in the number of loans per person), and in higher amounts (an increase of about 5% in average principal). These three variables all point to an increase in payday loan usage. The main measure of payday loan usage is total loan value (sum of principals), which shows an increase of about 20% when the fees go down.[18]

The estimates show that default (among individual loans) occurs 12% less often (which means decreasing from a base of 2% to 1.76%) as a result of the

[18]Since total loan value is equal to number of borrowers multiplied by number of loans per borrower multiplied by average principal, this increase (20%) could be achieved by adding the increase in each of those three variables.

Table 1.3: Regression Results for Average Principal (Adjusted) and Total Loan Value

Dependent Variable (log)	*Average Principal*					*Total Loan Value*				
Specification	(I)	(II)	(III)	(IV)	(IV)	(I)	(II)	(III)	(IV)	(IV)
Control Group	CG9	CG9	CG9	CG9	CG18	CG9	CG9	CG9	CG9	CG18
Baseline Value for RI	~ $370					~ $4M per Month				
POST x RI	**0.053 *****	**0.054 *****	**0.053 *****	**0.056 *****	**0.052 *****	**0.222 *****	**0.2 *****	**0.217 *****	**0.202 *****	**0.223 *****
	(0.003)	(0.002)	(0.003)	(0.003)	(0.008)	(0.012)	(0.011)	(0.011)	(0.013)	(0.04)
Personal Income	-	Y	Y	Y	Y	-	Y	Y	Y	Y
Unemployment Rate	-	Y	Y	Y	Y	-	Y	Y	Y	Y
State F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	-	Y	Y	Y	Y	-	Y	Y
Month F.E.	Y	Y	-	-	-	Y	Y	-	-	-
Month x State F.E.	-	-	-	Y	Y	-	-	-	Y	Y
Year x Month F.E.	-	-	Y	-	-	-	-	Y	-	-
State x Linear Trend	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R squared	99.8%	99.8%	99.8%	99.8%	99.2%	99.4%	99.5%	99.8%	99.4%	99.4%
Observations	600	600	600	600	1140	600	600	600	600	1140

Significance levels: *** (1%), ** (5%), * (10%)
Standard errors are clustered at the state level.
Critical values are based on T(G - L) distribution (Cameron and Miller, 2013).

Table 1.4: Regression Results for Average Default

Dependent Variable (log)	*Average Default*				
Specification	(I)	(II)	(III)	(IV)	(IV)
Control Group	CG9	CG9	CG9	CG9	CG18
Baseline Value for RI	2%				
POST x RI	**-0.13 ***** (0.034)	**-0.12 **** (0.043)	**-0.133 **** (0.048)	**-0.129 **** (0.051)	**-0.191 ***** (0.041)
Personal Income	-	Y	Y	Y	Y
Unemployment Rate	-	Y	Y	Y	Y
State F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	-	Y	Y
Month F.E.	Y	Y	-	-	-
Month x State F.E.	-	-	-	Y	Y
Year x Month F.E.	-	-	Y	-	-
State x Linear Trend	Y	Y	Y	Y	Y
Adj. R squared	91.9%	92.1%	93.2%	91.9%	92.8%
Observations	600	600	600	600	1140

Significance levels: *** (1%), ** (5%), * (10%)
Standard errors are clustered at the state level.
Critical values are based on T(G - L) distribution (Cameron and Miller, 2013).

Table 1.5: Regression Results for Characteristics of Borrowers

Dependent Variable (log)	*Average Income of Borrowers*					*Average Age of Borrowers*				
Specification	(I)	(II)	(III)	(IV)	(IV)	(I)	(II)	(III)	(IV)	(IV)
Control Group	CG9	CG9	CG9	CG9	CG18	CG9	CG9	CG9	CG9	CG18
Baseline Value for RI	$2200 per Month					41 Years				
POST x RI	**0.013 *****	**0.011 *****	**0.013 *****	**0.013 *****	**0.005**	**-0.007 *****	**-0.007 ****	**-0.007 ****	**-0.007 ****	**-0.008 ****
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Personal Income	-	Y	Y	Y	Y	-	Y	Y	Y	Y
Unemployment Rate	-	Y	Y	Y	Y	-	Y	Y	Y	Y
State F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	-	Y	Y	Y	Y	-	Y	Y
Month F.E.	Y	Y	-	-	-	Y	Y	-	-	-
Month x State F.E.	-	-	-	Y	Y	-	-	-	Y	Y
Year x Month F.E.	-	-	Y	-	-	-	-	Y	-	-
State x Linear Trend	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R squared	97.3%	97.4%	98.3%	97.2%	97.8%	97.5%	97.5%	98.3%	97.5%	98.3%
Observations	600	600	600	600	1140	600	600	600	600	1140

Significance levels: *** (1%), ** (5%), * (10%)
Standard errors are clustered at the state level.
Critical values are based on T(G - L) distribution (Cameron and Miller, 2013).

lower fees. This can be explained through two mechanisms. First, lower fees make rollover and repayment relatively less costly than defaulting. Second, if less credit-constrained consumers are attracted to the market when the fees go down, and assuming that such consumers are less risky, the ratio of consumers defaulting will also decrease. The slight increase in the average income of borrowers (as seen in Table 1.5) supports this hypothesis.

All specifications have high R-squares. This is because, first, the payday loan market has different scales across the states, and second, because the variables have apparent seasonality. Therefore, the state and time fixed effects alone explain a big portion of the variation in outcomes.

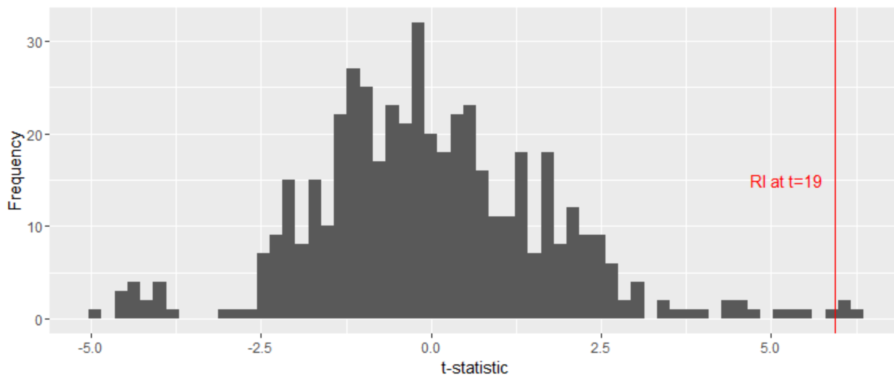
In the next three subsections, I examine the robustness of the estimates to placebo tests, use synthetic control, and show how the effects unfold over time. Because total loan value and default rate are the outcomes that I use in welfare analyses, the robustness checks focus on them.

1.5.1 Placebo Test

As a robustness check for the difference-in-difference analysis, I assume that the policy change happened in any of the 9 states in CG9 plus Rhode Island, in any period between 7 and 54. (I ignore the first and last 6 months so that there are enough pre- and post-periods.) I estimate the effect of each "treatment" on payday loan consumption, using equation (1.1) and ordinary (non-clustered) standard errors. This creates 480 (10 states $\times$ 48 periods) placebo estimates. Figure 1.5 shows where the actual treatment (Rhode Island in period 19) falls within the distribution of the t-stats. It turns out that the actual treatment ranks 4th in absolute value of the t-statistic among all treatment effects, making the probability of an impact this large happening by chance 0.8%. The three larger t-stats also belong to Rhode Island around the time of the policy change.

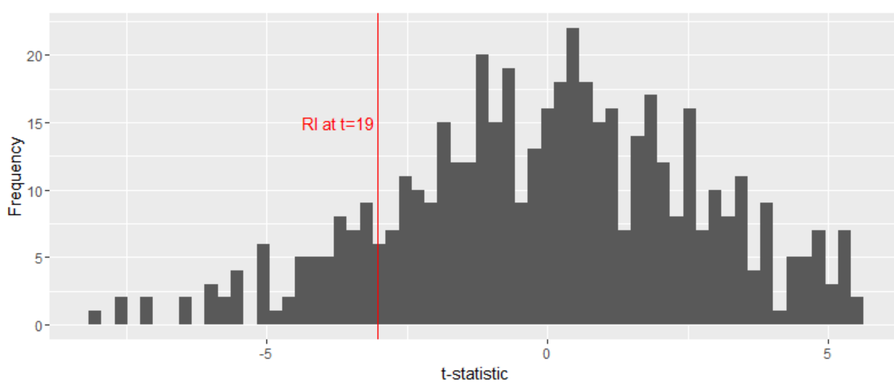
Performing the same analysis for average default shows that the actual treatment ranks 131st among 480 treatments (as depicted in Figure 1.6), in terms of the absolute value of t-statistic, making it about 27% likely that NR did not have an actual effect on default. For this reason, in section 6 when my analysis involves default, I perform it both with a decreasing default and a flat one, and show that the results are only slightly affected.

Figure 1.5: Distribution of Placebo Treatment Effects for Total Loan Value



The actual treatment (Rhode Island in period 19) is ranked 4th among 480 in terms of absolute value of t-statistic, making the probability of a change in total loan value this big happening by chance less than 1%.

Figure 1.6: Distribution of Placebo Treatment Effects for Average Default



The actual treatment (Rhode Island in period 19) is ranked 131st among 480 in terms of absolute value of t-statistic, making the probability of a change in default this big happening by chance less about 27%.

1.5.2 Synthetic Control Analysis

In this subsection, I follow the technique introduced by Abadie, Diamond, and Hainmueller (2010) to construct a synthetic control for Rhode Island: a weighted average of control units (states in CG18) that closely resembles pre-NR Rhode Island. Subsequently, I study how the real Rhode Island diverges from its synthetic version when the fee cap is lowered. I focus on only two outcomes, total loan value and average default (both in log transformation). For each outcome, the algorithm assigns weights to each state in such a way that the synthetic unit tracks the pre-treatment treated unit (Rhode Island) as closely as possible. This is achieved by finding the weights that minimize the Mean Squared Prediction Error for the pre-periods:

$$MSPE_{pre} = \frac{\sum_{1\leq t\leq T_{pre}} (Y_{treated,t} - Y_{synth,t})^2}{T_{pre}}$$

To make the synthetic unit even more similar to the treated group, weights can be adjusted so that the synthetic and the treated units have similar pre-treatment means in a few variables of choice, called predictors. That is,

$$\frac{\sum_{1\leq t\leq T_{pre}} X_{treated,t}}{T_{pre}} = \frac{\sum_{1\leq t\leq T_{pre}} X_{synth,t}}{T_{pre}} \quad for\ X \in Predictors$$

I choose the predictors to be Personal Income, and the ratio of subprime individuals to the state's population.

I first conduct the analysis for total loan value. Table 1.6 shows the weights assigned by the algorithm to each state in CG18 to construct the synthetic Rhode Island. North Dakota and Wyoming are the main contributors while the other states receive weights below 10% each. These weights give the synthetic unit equal pre-NR predictor means to those of Rhode Island. Figure 1.7 (A) compares the time path of total loan value between RI and the synthetic unit, while Figure 1.7 (B) displays the gap between the two paths.

To show that Rhode Island's divergence from its synthetic version after NR is not a coincidence, *a la* Cunningham and Shah (2014), I make a synthetic unit for all states in CG18. Next, for each state I find the ratio of the post-NR MSPE to the pre-NR MSPE. For a state that tracks its synthetic unit closely before the treatment and greatly diverges from its synthetic unit after the treatment, this ratio will be large. For a state that always remains close to its synthetic

Table 1.6: Weights Used to Construct the Synthetic Rhode Island

State	AL	CA	FL	IA	ID	IN	KS	LA	MI
Weight for Total Loan Value	.029	.036	.028	.068	.051	.031	.045	.022	.042
Weight for Average Default	.032	.034	.032	.046	.042	.033	.044	.028	.038
State	MO	ND	NE	NV	OK	SD	TX	UT	WY
Weight for Total Loan Value	.039	.199	.076	.015	.030	.084	.028	.057	0.122
Weight for Average Default	.037	.299	.047	.024	.033	.049	.031	.044	.111

version, this ratio will be small. Figure 1.7 (C) shows the gap between each state and its synthetic version. Rhode Island displays the biggest change after the treatment. Figure 1.7 (D) shows the distribution of $\frac{MSPE_{post}}{MSPE_{pre}}$ among all states in CG18. RI has a ratio of 54.6 while the second largest ratio is 37. The probability of RI having the largest ratio by chance is 1/19, or 5.26%.

I repeat the above analysis for average default. Table 1.6 shows the weights given to states to make a synthetic unit that closely tracks pre-NR average default in Rhode Island. Figures 1.8 (a)-(b) compare the average default between RI and its synthetic version. Finally, Figure 1.8 (c) shows the distribution of post-MSPE to pre-MSPE ratios among the states. This ratio is 2.004 for RI, which makes it the 12th largest one, implying a p-value of 0.63. This is consistent with the result from the placebo test in which the effect of NR on default was found statistically insignificant.

The results of the synthetic control analysis, in line with the placebo tests, asserts that the increase in loan consumption is a consequence of the lower fees. A strong statement cannot be made about the decrease in default.

1.5.3 Progression of the Effects

The progression and persistence of the effect of lower fees on payday loan usage is important in regard to the welfare analysis. To measure these characteristics, I estimate a variant of equation 1.1:

$$log(Y_{st}) = \alpha_0 + \mu_s + \phi_{\mathrm{y}(t)} + \gamma_{\mathrm{m}(t)} + \lambda_s t + \beta X_{st} + \delta POST(t) +$$
$$\triangle_1 \, \mathrm{POST}_{1,6}(t) \, \mathrm{RI}(s) + \triangle_2 \, \mathrm{POST}_{7,18}(t) \, \mathrm{RI}(s) + \triangle_3 \, \mathrm{POST}_{19,30}(t) \, \mathrm{RI}(s) + \triangle_4 \, \mathrm{POST}_{31,42}(t) \, \mathrm{RI}(s) + \epsilon_{st}$$

In this equation, $\mathrm{POST}_{a,b}(t)$ is equal to 1 for observations which are a to

Figure 1.7: Synthetic Control Analysis for Total Loan Value

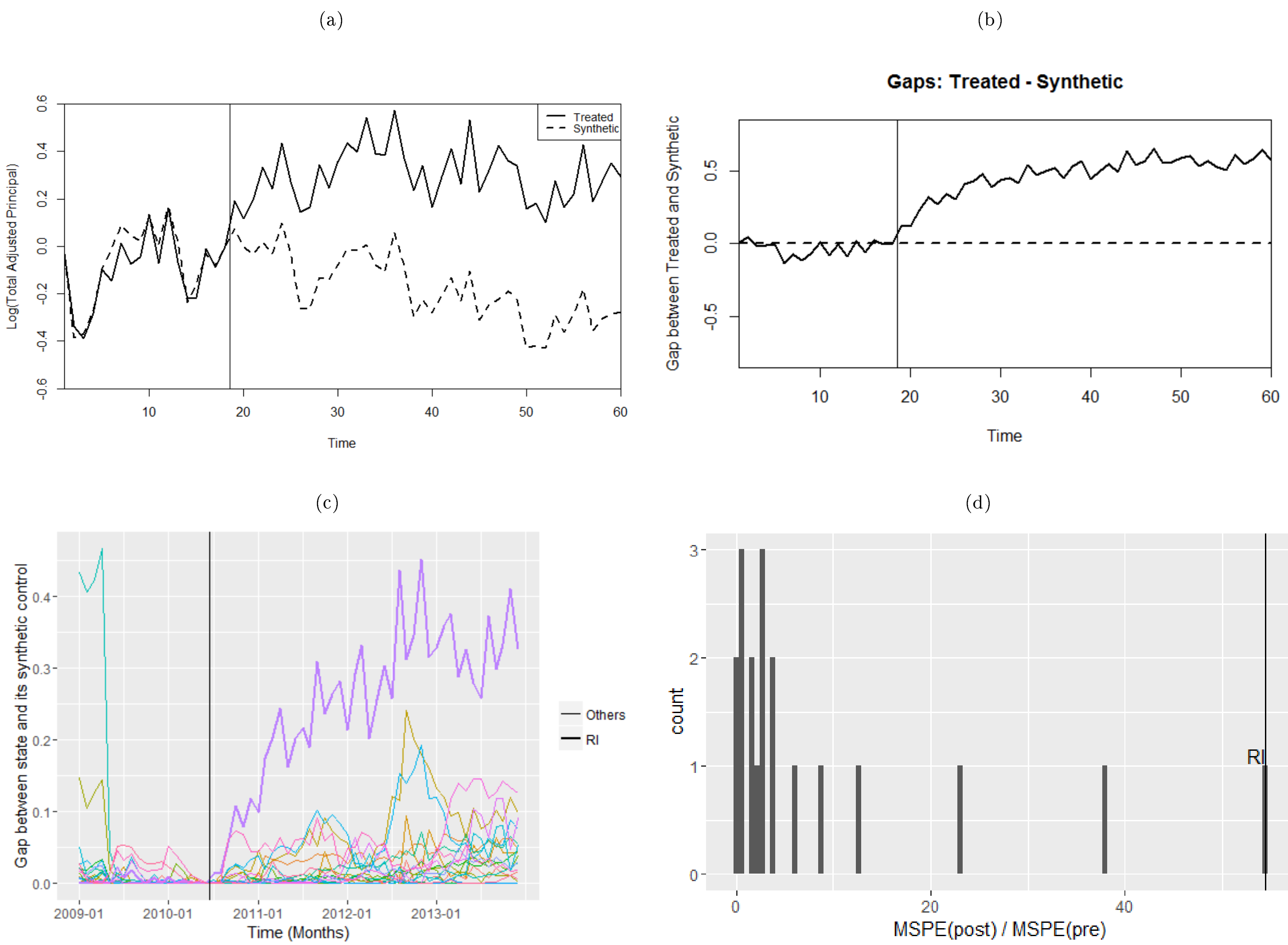
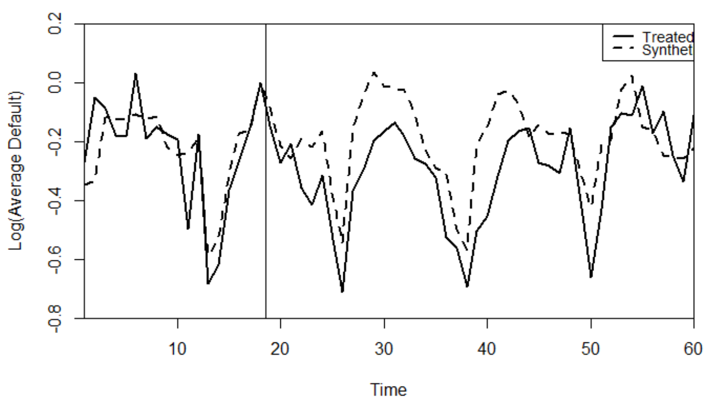
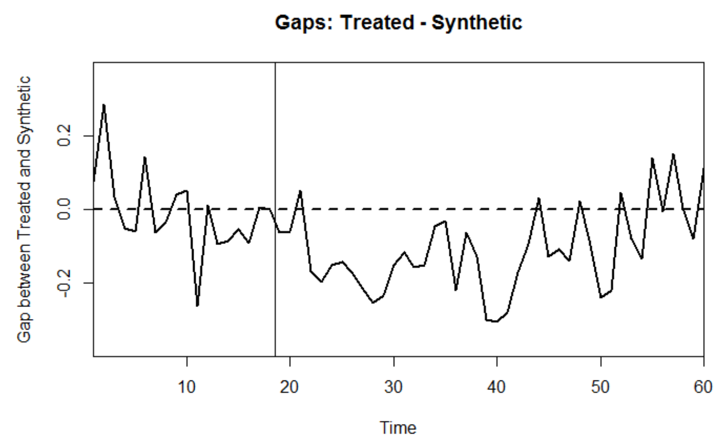


Figure 1.8: Synthetic Control Analysis for Average Default

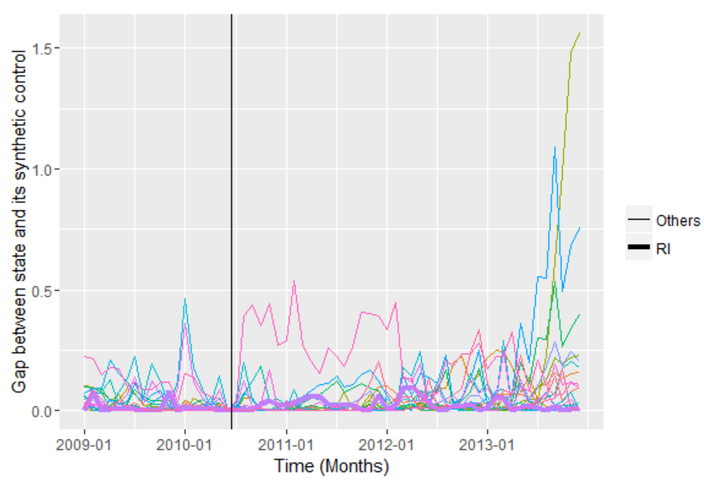
(a)



(b)



(c)



(d)

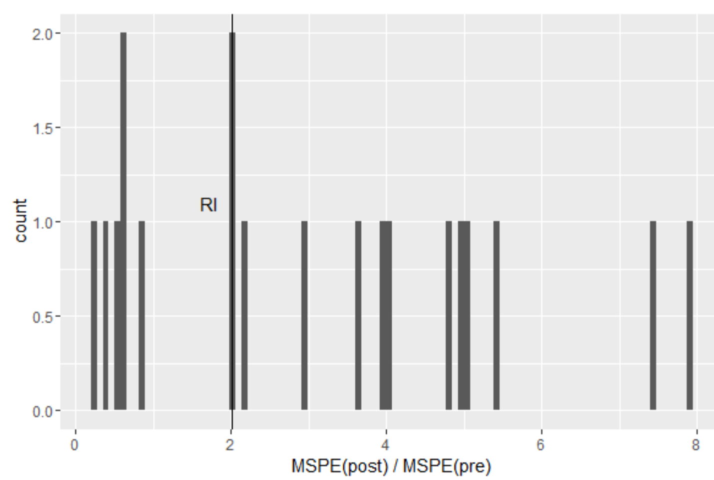
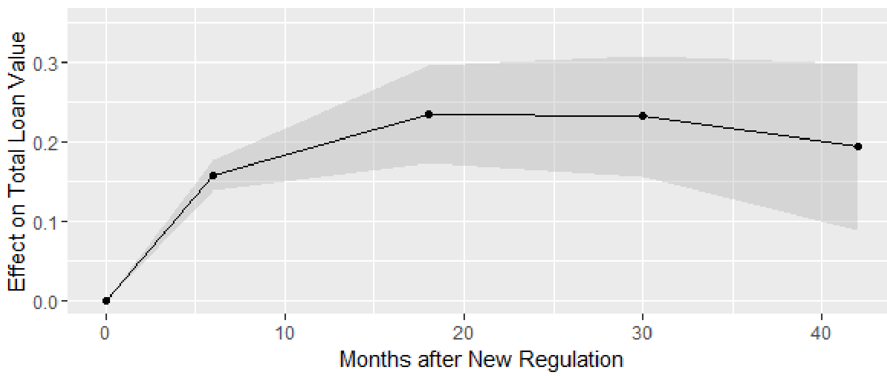


Figure 1.9: Evolution of the Effect on Total Loan Consumption



The gray band represents a 95% confidence interval around the estimated effects. The effect starts to show up immediately and persists over time.

b months after NR, and zero otherwise.[19] Therefore, $\triangle_1, \ldots, \triangle_4$ estimate the effect of lowering the fees on total loan value, 6 months after NR (Jul-2010 to Dec-2010), 7 to 18 months after NR (Jan-2011 to Dec-2011), 19 to 30 months after NR (Jan-2012 to Dec-2012), and 31 to 42 months after NR (Jan-2013 to Dec-2013), respectively.

Figure 1.9 displays the evolution of the effect over time. By the end of 2010, 6 months after NR, payday loan usage increases by about 15.7%. In the subsequent years, the effect stabilizes at around 20%, although the further in time we move, the less precise the estimates become.

1.5.4 Changes to Loan Sequences

Having learned that lower fees result in higher payday loan usage, it is interesting to see how the structure of loan sequences are affected. In total, we have 60 months of data, of which 18 months belong to the pre- and 42 months belong to the post-treatment period. This makes comparing the sequences before and after the treatment challenging, because the post-treatment sequences are censored from above at a higher level, and can be longer by construction. Since a sequence could have started before period 1, and could have continued after period 60, I remove the sequences that start in the first month, and the ones that end in the last month. As a result, the pre-NR sequences start and end between

[19] Please note that the $\text{POST}_{a,b}(t)$ variables align perfectly with $\text{POST}(t)$ and the yearly fixed effects. So there is no need to include them in the equation separately.

Table 1.7: Effect of Lower Fees on Loan Sequence Structure

Dependent Variable	*log(Number of Loans in Seq.)*	*log(Duration (in days) of Seq.)*	*log(Fees Paid per $100 in Seq.)*	*Sequence Ends with Default*
Control Group	CG9	CG9	CG9	CG9
Regressors				
POST x RI	**0.254 *****	**0.203 *****	**- 0.086 *****	**0.024 *****
	(0.018)	(0.019)	(0.010)	(0.006)
Personal Income	Y	Y	Y	Y
Unemployment Rate	Y	Y	Y	Y
State F.E.	Y	Y	Y	Y
Start Year F.E.	Y	Y	Y	Y
Start Month F.E.	Y	Y	Y	Y
State x Linear Trend	Y	Y	Y	Y
Adj. R squared	3.7%	4.8%	5.5%	1.2%
Observations	8,331,722	8,331,722	8,331,722	8,331,722

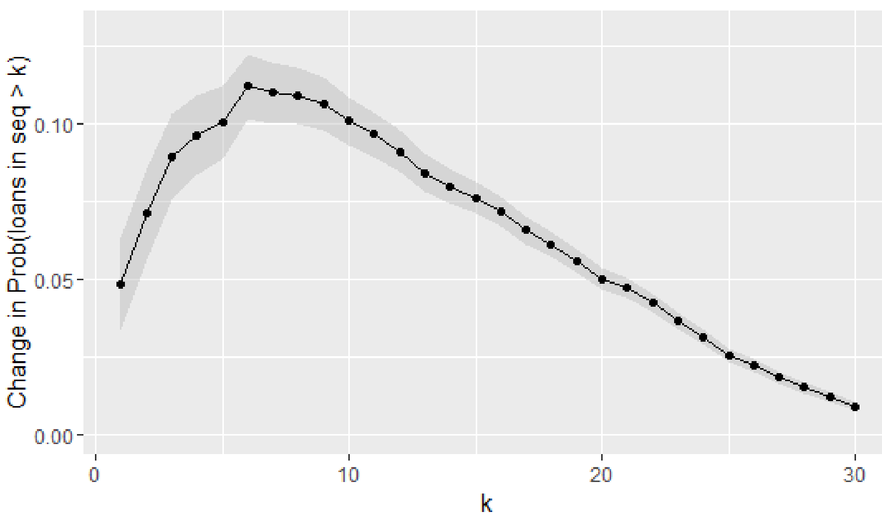
Significance levels: *** (1%), ** (5%), * (10%)
Standard errors are clustered at the state level.
Critical values are based on T(G - L) distribution (Cameron and Miller, 2013).
Each observation is a Loan Sequence.

periods 2 and 18 (or $[2, 18]$), which includes 17 months. To make the post-NR sequences comparable to the pre-NR ones, I only keep the sequences that start and end inside intervals of 17 months after NR, that is, the sequences whose whole "lifetime" is inside time intervals $[19, 35]$, $[20, 36]$,... , $[43, 59]$. After imposing this sample restriction, I use a regression equation similar to 1.1, but at the sequence level (q), in which the subscript t refers to the time the sequence started.

$$Y_{qst} = \alpha_0 + \mu_s + \phi_{\mathrm{y}(t)} + \gamma_{\mathrm{m}(t)} + \lambda_s t + \beta \boldsymbol{X}_{st} + \delta \,\mathrm{POST}(t) + \Delta \,\mathrm{POST}(t)\,\mathrm{RI}(t) + \epsilon_{qst} \tag{1.2}$$

In this equation, Y_{qst} is a characteristic of the sequence q that started at time t in state s. When the variable of interest is the log of the number of loans in the sequence ($Y_{qst} = \log(n_q)$), and when it is the log of the length (in days) of the sequence ($Y_{qst} = \log(d_q)$), the estimates show an increase of 25% and 20%, respectively, as presented in Table 1.7. This shows that lower fees make sequences considerably longer.

Figure 1.10: Effect of Lower Fees on Distribution of Number of Loans in Sequence



Each point is a difference-in-difference coefficient obtained from estimating equation (1.2) with $y_{qst} = 1(n_q > k)$, in which n_q is the number of loans in sequence q. Observations are sequences from Rhode Island and CG9. The bands represent a 95% confidence interval. This graph shows that about 0.11 of probability mass shifts from sequences with 6 or less loans, to sequences with more than 6 loans.

In addition to the average changes, it is important to see how the distribution of loans per sequence changes. I define $Y_{qst} = 1(n_q > M)$ in equation 1.2, and run a separate regression for M ranging from 1 to 30. Figure 1.10 shows the estimation results for these regressions. This figure demonstrates that about 0.11 of probability mass shifts from the sequences with 1 to 6 loans to those with 7 or more loans.

Longer sequences are an unintended consequence of the lower fees and can negatively affect borrowers. For example, suppose that a borrower would rollover a \$400 loan 3 times when the fees are 15%[20]. This means that she would pay a total of $4 \times (\$400 \times 0.15) = \$240$ in fees. If she would rollover the same loan 5 times with 10% fees, she would pay $6 \times (\$400 \times 0.1) = \$240$ in fees again. In this imaginary case, the lower fees do not benefit the individual. To see whether borrowers pay more or less for a sequence after NR, I define $Y_{qst} = n_q \times \text{fee}_t$ in equation 1.2, in which fee_t is the prevailing fee at time t. The estimates,

[20]This constitutes a sequence of 4 loans, that is, the initial loan plus the following 3 loans.

presented in the third column of Table 1.7, show that consumers pay about 8% less for each sequence. This number makes sense, because the fee for each loan went from 15% to 10%, or a 33% decrease, while the number of loans per sequence showed a 25% increase. The net effect on total sequence fees would be 8%. This is an interesting result, indicating that a big part of the decrease in fees is canceled out by the longer sequences.

Finally, the results show that after the policy change, debt cycles become 2.4 percentage points more likely to end with default. This is interesting because I showed before that default at the individual loan level (counting each rollover as a separate loan) goes down. Imagine a scenario in which a borrower is subject to a consumption shock each period, and defaults when she receives a large shock while already in debt. In this case, the longer the debt cycle, the more likely is the borrower to receive a large shock, and hence, to default.

1.5.5 The Online Market

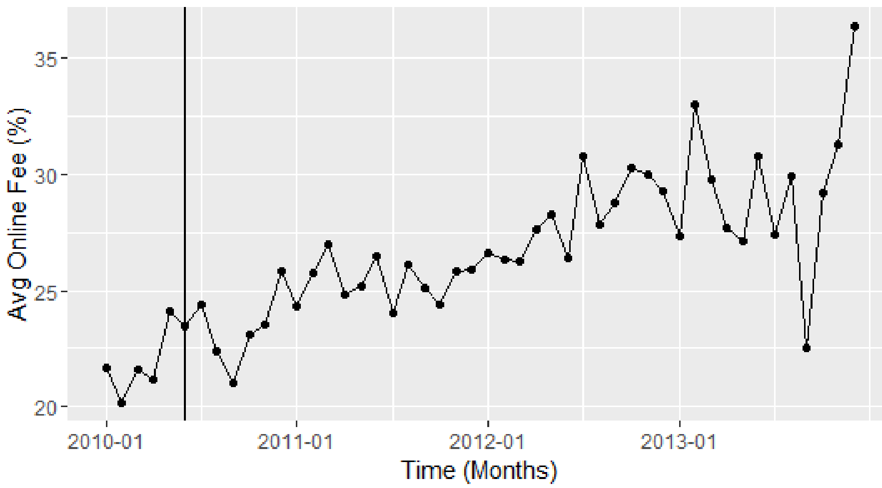
In addition to the storefront payday loan market, there is an online market[21] whose actual size is unknown, but according to a Pew Institute survey, is used by one quarter of payday loan borrowers Bourke, Horowitz, and Roche (2012). If the online market followed the same rules as the storefront market, I could generalize my results to the whole payday loan industry. In reality, however, pricing for online loans tends to not abide by state-sanctioned caps, because, many online payday lenders claim to be exempt from state lending laws and licensing requirements.[22]

I obtained a sample of online payday loans between 2010-2013 from a subprime credit bureau. According to the bureau's estimate, this dataset covers about 5-10% of the online market during that time frame. As seen in Figure 1.11, when the fee cap was 15%, online lenders charged Rhode Island residents upwards of 20%. When the cap was lowered to 10%, the online fees were not affected and kept an upward trend. As displayed in Figure 1.12, the number of online loans also seems to be unaffected by NR around the time of the change. These graphs suggest that the online market is separate from the storefront market, and that there is not a considerable substitution from the online market to the storefront market when the fees go down. One possibility is that the online

[21]For an online payday loan, instead of a post-dated check, the borrower gives the lender electronic access to their bank account.

[22]Such lenders identify as offshore or tribal.

Figure 1.11: Online Payday Loan Fees for Rhode Island Borrowers



Many lenders in the online payday loan market identify as offshore/tribal, and do not abide by the state laws (including fee caps). The fees are higher than the storefront market, and do not seem to be affected by the imposition of lower fee caps in mid-2010 (the vertical line).

market is used by borrowers who are excluded from the storefront market after defaulting their loans.

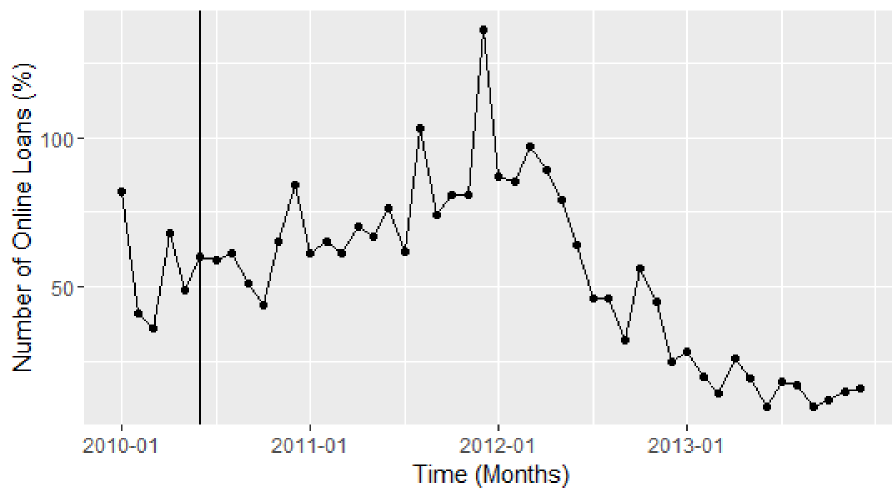
1.6 Analysis of Demand and Surplus

With neoclassical agents, a decrease in price always increases consumer surplus. To calculate this increase, I need an estimate of the market demand function. In addition, to approximate the change in producer surplus (PS) and efficiency (total surplus), industry marginal cost (MC) is also required. The reduced form results from the previous section, combined with a few assumptions that are supported by the data, can be used to estimate these two functions.

In the previous section, I showed that the lenders charged 15% in fees when the cap was 15%, implying that the fee would have been higher absent any cap. Moreover, no stores leave the market at 10% fees, implying that the the firms stay profitable at this price. These two observations suggest that the lenders had significant market power.

To estimate the MC function, it is important to understand the costs the lenders face. Flannery and Samolyk (2005) surveyed 600 stores (two monoline

Figure 1.12: Number of Online Payday Loans Taken Out by Rhode Island Residents



The number of online loans taken out by Rhode Island residents does not seem to be affected around the time of the policy change (indicated by the vertical line). There is a drop in the number of online loans in late 2012, but it is too far in time to be attributed to the change in price cap in 2010.

lenders, and 300 stores each) within the US about their costs and revenues in 2002-2004. They summarize major operating costs for mature stores (in business for more than 4 years) as seen in Table 1.8. By definition, MC is the cost to the lender of making an additional \$100 loan. Among the major costs of lenders, loan losses (cost of default) seem to be more likely to be marginal, in the sense that for each additional \$100 loan, the loan loss is $\Pr((default)) \times \$100$ in which $\Pr((default))$ can be thought of as the historic average default rate in the market. Other costs such as wages and salaries, rent, maintenance, utility, and taxes are less variant. For example, when the number of loans issued by a store increases, unless they had been operating close to full capacity before, there would be no need to hire new staff or to move to a bigger store. The other category of the costs, loan collection expenses, is too small to have any economic significance. Assuming that loan losses are the major contributors to MC has two implications: first, since the default rate is around 2% in Rhode Island, the level of MC (about 2\$ per \$100 loan) is much lower than the the level of price caps (\$10 per \$100 loan). Second, as shown in the previous section, since the default rate does not increase with the lower fees, neither does MC.

Table 1.8: Main Operating Costs of a Payday Loan Store, Flannery and Samolyc (2005)

Cost Type	% Operating Costs
Wages and Salaries	39.80 (7.75)
Loan Losses	21.1 (9.6)
Rent, Maintenance, Utility and Taxes	17.3 (5.0)
Advertising	5.6 (3.7)
Loan Collection Expenses	1.3 (1.1)
Other Store Expenses	14.8 (5.2)
Total Costs	100

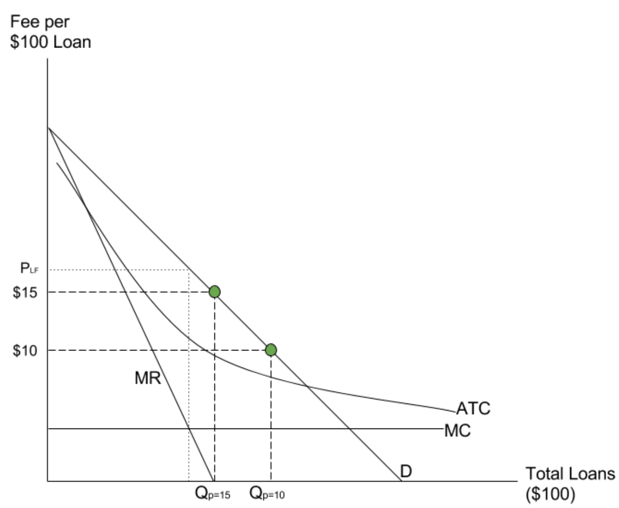
Flannery and Samolyc (2005) surveyed 600 payday loan stores pertaining to their costs and revenues. This table summarizes their findings on the main operating costs of a payday loan store.

These two arguments (that the lenders have market power and the level of MC is lower than the fee caps) suggest that the payday loan market setting should resemble the one depicted in Figure 1.13. In such a market, if there were no price caps, the lenders would set their price by setting marginal revenue (MR) equal to MC. With a price cap $\bar{P}$, the lenders would choose their supply (Q) by setting $MC = \bar{P}$. However, since the level of MC is lower than $\bar{P}$ for all quantities, MC and $\bar{P}$ never intersect, and the lenders supply as much as is demanded at $\bar{P}$. This means that the two $(Q, \bar{P})$ pairs, $(Q_{\bar{p}=15}, 15)$ and $(Q_{\bar{p}=10}, 10)$ trace out the demand curve. The fact that no store left the market when the cap was lowered to \$10 indicates that at $Q_{\bar{p}=10}$, Average Total Cost (ATC) remains below \$10.

I set total (monthly) loan value when the fee is 15% to 4 million dollars ($Q_{p=15} = \$4,000,000$), which is the average predicted total loan value for Rhode Island in each month between 2009 and 2013, assuming NR did not happen (POST(t) $= 0$ in equation (1.1)). In section 3, I estimated the increase in total loan value to be about 20% after NR, using various specifications and control groups. Hence, $Q_{p=10} = 1.20 \times Q_{p=15} = \$4,800,000$. With these two points on the demand curve and assuming that demand is linear between them, it is straightforward to calculate the change in consumer surplus. This change is shown by the blue region in Figure (1.14) and is equal to $\triangle CS = \$220,000 \times 12 =$ $2,640,000$ dollars, annually. To estimate the increase in CS relative to the pre-NR base, I have to impose an assumption on the shape of the demand curve for $Q \leq Q_{\bar{p}=10}$. Assuming linearity, this increase would be around 44%.

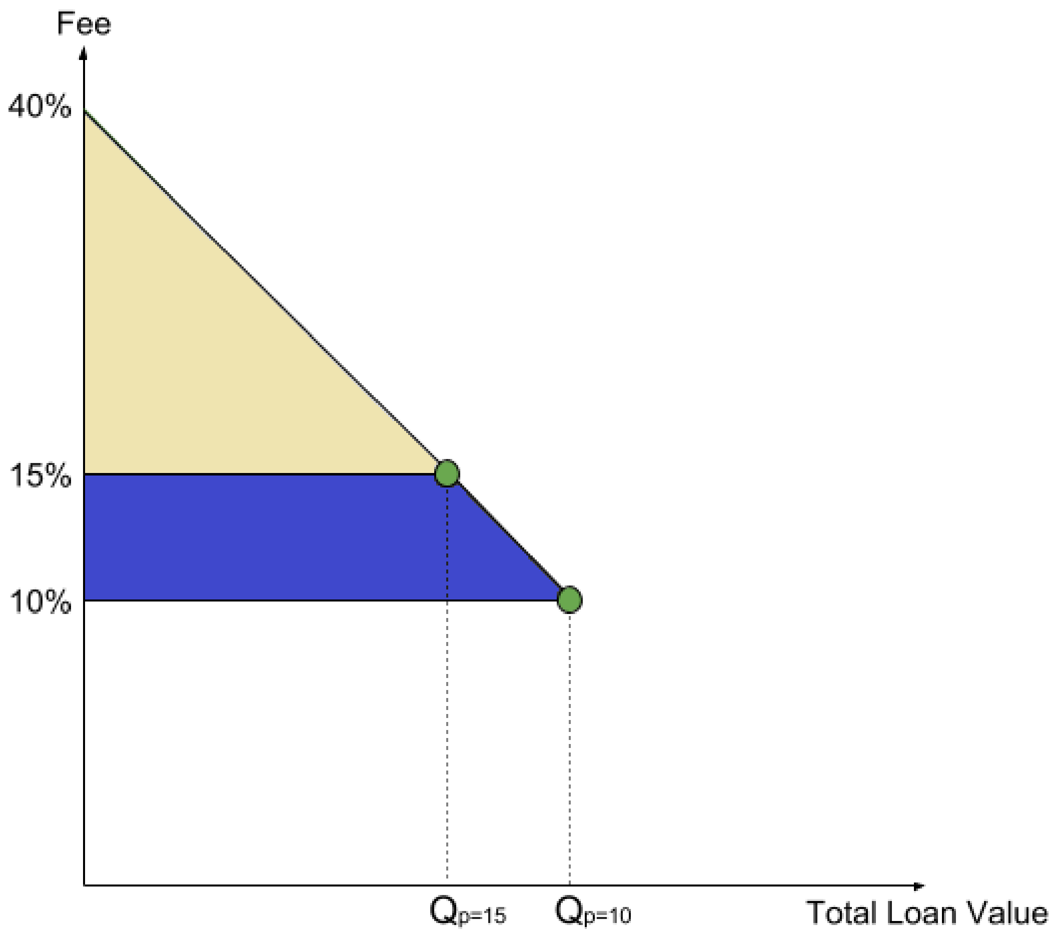
Although we do not know the exact marginal cost, but proceeding with the

Figure 1.13: Market for Payday Loans



This figure depicts the market settings for payday loans in Rhode Island, based on the reduced-form results. There is market power, so the unconstrained equilibrium price would be higher than 15%. MC has a lower level than the fee caps, so the quantity for each fee cap is determined by the market demand, not MC. At 10% fees, ATC is lower than 10%, so no lender leaves the market.

Figure 1.14: Change in Consumer Surplus



This graph depicts the increase in consumer surplus (the blue area) when the fees go down. The relative increase in CS would be the blue area divided by the yellow area.

Table 1.9: Fees Charged by Lenders in States with No Fee Caps in 2009-2013

State	Fees Charged (%)		
	Q1	Median	Q3
Delaware	20	20	20
Idaho	20	20	22
Missouri	19	19	19
Nevada	18.5	18.5	20
South Dakota	19	19	22
Utah	20	22	22

assumption that the cost of default represents MC, and that it stays flat at 2% after NR, the change in producer surplus is calculated to be $\triangle PS = -136,000 \times 12 = -1,632,000$ dollars, or a 26% decrease. Alternatively, consistent with the regression results, I assume that MC is downward sloping for $Q \leq Q_{\bar{p}=10}$. In this case MC goes down from 2% to 1.76% when the fee changes from 15% to 10%. The change in producer surplus is calculated to be -1,620,000 dollars annually, or a 27% decrease. Therefore, whether we assume MC is flat or slightly downward sloping does not make much difference about the change in PS.

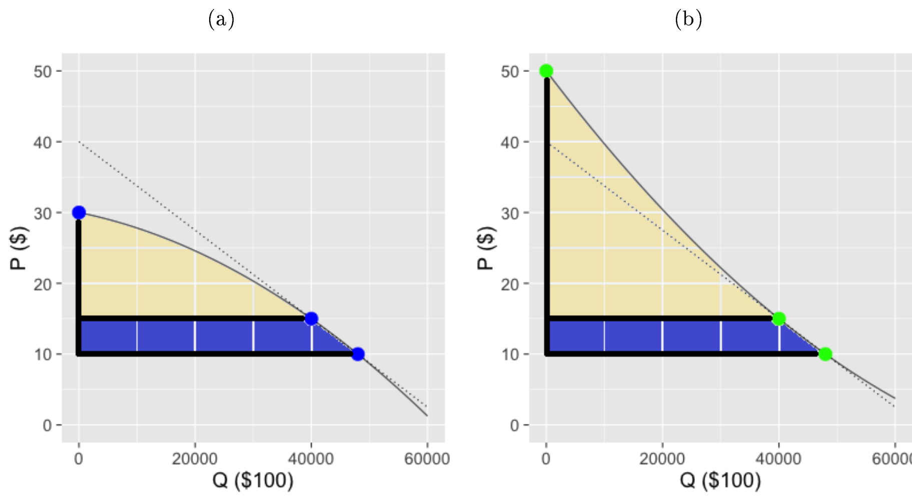
The 44% increase in CS and the 26% decrease in PS combined result in an 8% increase in market efficiency.

Even though assuming linear functional forms for demand and MC are simplistic, there are two pieces of evidence that suggest that they provide reasonable estimates of the actual functions. First, the linear demand function has an intercept of 40%, which indicates the maximum willingness to pay for these loans in the market. This number seems reasonable considering anecdotal evidence that loan sharks, the alternative option for a desperate loan-seeker, charge about 40% for a two-week loan. Second, this linear demand and MC (no matter if flat or slightly downward-sloping) generate[23] an unconstrained equilibrium fee of about 21%, which is strictly consistent with the fees the lenders charge in states with no fee caps, as presented in Table 1.9. Among states with no fee caps, Delaware is the most similar to Rhode Island in terms of size, population and region, and the lenders charge a 20% fee.

To see how sensitive the estimated changes in CS are to the linear assumption, I repeat the analysis with two quadratic demand functions. To fit a quadratic function, 3 points are required but only 2 are identified by the change

[23]This is calculated by setting the marginal revenue derived from the demand function, equal to MC.

Figure 1.15: Non-linear Demand Functions



These graphs show the change in consumer surplus if the demand had a quadratic form, and the maximum willingness to pay for payday loans was 30% (the left graph) and 50% (the right graph). The dotted lines show the linear demand for comparison. The absolute change in consumer surplus (the blue part) is almost the same in both graphs, but the relative improvement (blue area divided by the yellow area) depends on the demand shape, and is about 60% for the left graph and 30% for the right graph.

in fee cap. The linear function has an intercept of 40%. For the quadratic functions, I assume an intercept of 30% (which creates an outward-curved function, as shown in Figure (1.15) (a)), and 50% (which creates an inward curved function, as shown in Figure (1.15) (b)). With these functions, the increase in CS is almost similar to the amount calculated with the linear demand ($2.6 million), however, the relative change in CS is 62% and 34%, respectively. The implied unconstrained equilibrium fees are 19% and 24%, respectively.

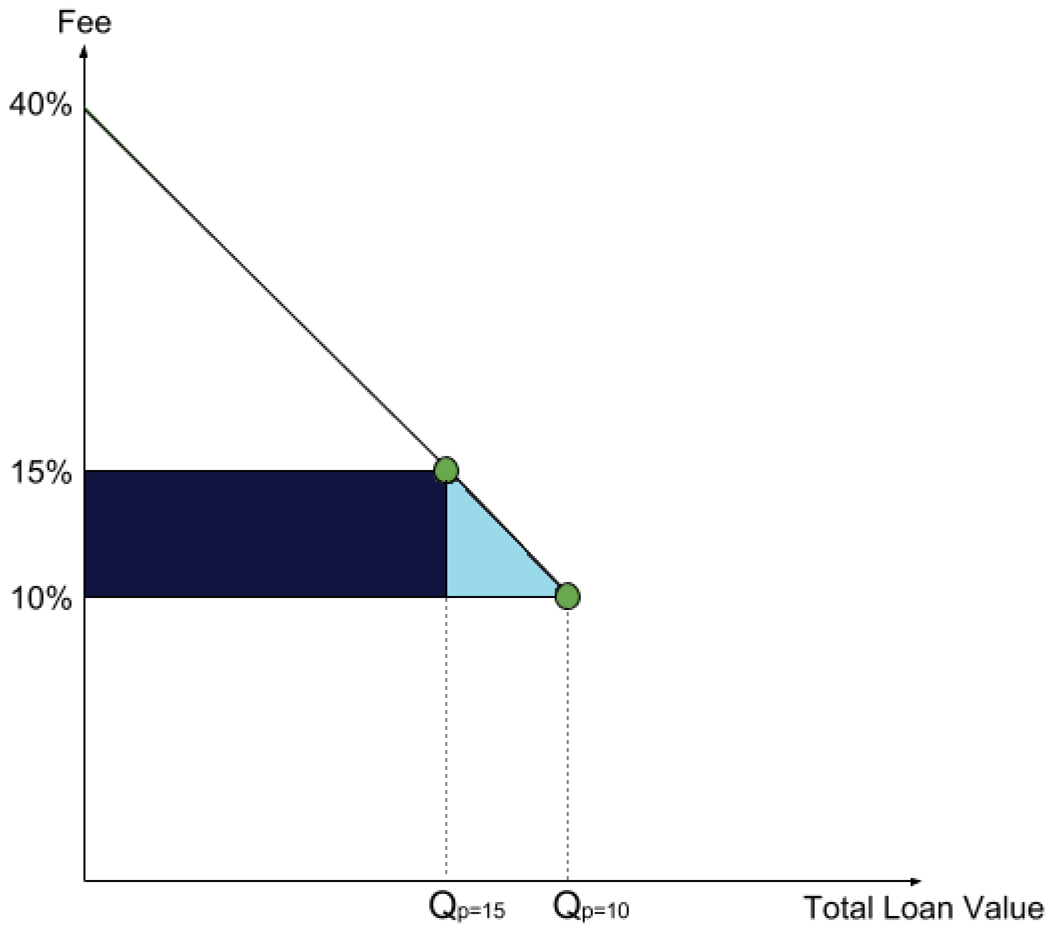
The calculations above are based on the assumption that the observed demand function is the outcome of the borrowing decisions of neoclassical consumers. If this assumption is not true, there are still things that can be learned from this analysis. Violation of the neoclassical assumption makes the calculated 44% an upper bound for the actual improvement in CS. Looking at Figure (1.16), we can break the increase in "consumer surplus" into two parts. The first part, colored in dark blue, shows that keeping the quantity fixed at its initial level ($Q_{p=15}$), the borrowers would pay $2.4 million less annually for the same amount of loans. This is a direct transfer from the lenders to the borrowers and would definitely make the consumers better off. The triangular part, colored in light blue, represents the new borrowers and the increased borrowing by the old borrowers, and amounts to $240,000 additional spending on payday loans each year. This is the part that can potentially be welfare-decreasing if it is the result of irrational (time-inconsistent) behavior. Since the size of the triangle is 10% of the size of the rectangle, for the policy change to make consumers better off, the welfare gain from one dollar transferred to the borrowers should be at least one tenth of the welfare loss resulting from one extra dollar spent on payday loans. Using the current analysis, there is no way of knowing whether this is true or not. For this reason, in the next chapter I develop a theoretical model of payday loan consumption, and simulate the effects of lowering the fees on consumer welfare.

1.7 Conclusion

As payday loans remain an important concern to state and federal policy makers, it is necessary for researchers to shed light on the consequences of different types of regulation in this market. In this paper, I looked closely into an instance of such regulations, namely, tightening the cap on payday loan fees. The legislation decreased the fee cap on payday loans from 15% to 10% in Rhode Island in mid 2010. This legislation directly addressed one of the main concerns with payday loans (high APRs)[24] but not the rest of them, such as excessive rollovers that result in debt traps. As shown in the paper, this policy change resulted in an increase in the number of borrowers, the average amount of the loans, and the length of loan sequences. If we assume that payday loans are like any other good and that consumers are rational, lower prices undoubtedly lead to higher consumer surplus. I calculated this increase to be about 44%. However, many law-makers believe that payday loans are harmful products by nature, especially since they target the subprime population who are less financially educated and more vulnerable to making decisions that are not optimal in the long-run. If that is indeed the case, then we should take into consideration the potential negative effects that can arise from the higher usage caused by the lower fees. This would make the calculated efficiency gains from the cheaper loans an upper bound for actual welfare improvement.

[24] It should be noted that a $10 fee per $100 loan is still considered high by consumer rights activists because it generates an APR above 36%.

Figure 1.16: Decomposing the Change in Consumer Surplus



This graph shows the two components of the change in CS. The rectangular part (in dark blue) represents a transfer from lenders to borrowers, and is definitely welfare improving for consumers. The triangular part (in light blue) depicts the additional spending on payday loans as a result of lowering the fees. If this is a behavioral demand (in contrast with a neoclassical demand), the rectangular section can potentially be welfare-decreasing if it is a result of "over-borrowing." The size of the triangle is one tenth of the rectangle.

Chapter 2

Payday Loan Regulation with Time-inconsistent Consumers: Evidence from Rhode Island

2.1 Introduction

Many policy makers and consumer rights advocates believe that payday loans are harmful to the financial well-being of consumers. As a result, most US states have imposed some form of restriction on lenders. As of 2017, interest rate caps and payday loan prohibitions are the most widespread types of payday loan regulation. If we assume that consumers are neoclassical (specifically, time-consistent or without present-bias), it follows that a tighter interest rate cap certainly makes consumers better off by making the loans more affordable. This assumption also implies that banning the loans is welfare-decreasing because it makes consumers more credit constrained.

Payday loans are used largely by subprime consumers who are believed by many policymakers to be more vulnerable to temptation, and to making decisions that would hurt them in the long-run. This highlights the potential importance of going beyond the neoclassical assumption to acquire a more complete view of the welfare consequences of payday loan regulations. For this reason, I perform a behavioral welfare analysis in this chapter, assuming that the consumers can potentially have present bias and make time-inconsistent decisions. Such consumers tend to borrow even in the absence of bad (income/consumption) shocks and to procrastinate on repaying the loans to keep their current consumption high while disregarding future consequences. In this case, lowering the fee cap can potentially be welfare-decreasing because it further encourages time-inconsistent behavior. Similarly, a ban can be welfare-improving because it protects consumers from overborrowing.

I develop a dynamic model of payday loan usage with naïve-hyperbolic discounting, *a la* Skiba and Tobacman (2008), and calibrate it in such a way that the simulated means are as close as possible to the empirical means in Rhode Island, both when the fee cap was 15% and when it was 10%. The fact that the model is calibrated to imitate the data under two different regimes (10% fees and 15% fees) makes it more reliable than simple calibrations that are not identified off of a policy change. I find that the behavior of the average payday loan user in Rhode Island is consistent with a hyperbolic discount factor of about 0.6. Nonetheless, even accounting for this time-inconsistency, simulations of the model imply that for all borrowers lower fees are welfare improving, suggesting that the welfare gain from the lower cost of the loans outweighs the welfare loss from the heightened time-inconsistent behavior. Simulations also suggest that for the average consumer and those who are more time-inconsistent than average, removing the market (prohibiting payday loans) is more welfare improving than lowering the fee cap to 10%, but the rest of consumers (those with lower degrees of time-inconsistency) would be harmed by such a policy. In the end, what type of regulation (between a fee cap and a ban) is preferred depends on the weights assigned to consumers with and without present bias in the social welfare function.

The economic literature on payday loans is mainly focused on how access to the loans affects variables such as Chapter 13 bankruptcy (Skiba and Tobacman, 2009), paying mortgage, rent and utility bills (Melzer, 2011), or home foreclosures and property crime after natural disasters (Morse, 2011). Therefore, the results of these papers can guide policymakers only when deciding to prohibit the loans. My paper stands out in this literature because it compares the welfare consequences of the two major forms of regulation (bans and fee caps) within the same framework. The welfare analyses executed in this paper are unique in the realm of payday loan research in the sense that, instead of measuring the changes in variables that can be correlated with consumers' financial well-being, I measure consumers' lifetime utility. For this reason, my analyses provide a more holistic view of the welfare implications of a regulation.

These results are important for the ongoing efforts to regulate consumer credit markets, particularly when neoclassical assumptions are not likely to hold.

The rest of the paper is structured as follows: In section 2, the theoretical model is laid out. Section 3 includes model calibration. Simulation results and welfare analyses are presented in section 4. Section 5 concludes.

2.2 Theoretical Model

The model is built upon Skiba and Tobacman (2008) finding that naïve hyperbolic discounting is the most compatible with the behavior of payday borrowers in their data[1], compared to exponential discounting and sophisticated hyperbolic discounting. The model I develop is inherently similar to the one developed by these authors, but in addition, is tailored for the institutional settings of the Rhode Island market, and incorporates the discreteness of the choice between re-paying, rolling over and defaulting a loan (instead of a continuous choice about the change in the current loan balance).[2]

I develop the model only for a borrower who is paid bi-weekly or semi-monthly, for two reasons. First, the median pay frequency and the median loan duration are 14 days in the sample. Second, Skiba and Tobacman (2008) focus only on bi-weekly loans as well. The details of the model and the parameter values are laid out below.

The consumer's state in each period (S_t) is described by four variables: the consumption shock (ε_t), wealth (or saving) (W_t), ever defaulted (D_t), and payday loan balance (L_t).

$$S_t = (\varepsilon_t, W_t, D_t, L_t)$$

Every two weeks the person receives a fixed expected income (Y). I set $Y = \$1100$, because borrowers have a median monthly income of about \$2200 in the sample. A bad consumption shock is a proportion of the income that is consumed in the beginning of the period for unexpected/unplanned reasons such as a car repair, medical bill, etc. A good shock can be interpreted as an unplanned decrease in consumption or increase in income. A consumption shock can have any value, even many times as large as the consumer's income.

[1] Payday loans from one lender in Texas issued during one year.

[2] This discreteness is a consequence of the lack of amortization in the payday loan market, discussed in more detail in section 3.

However, considering the small amount of payday loans (which cannot exceed \$500 in Rhode Island), these loans are not able to significantly ease financial hardships after very large shocks. Because of this, as well as computational reasons, I assume the shock can take 7 possible values. Large (good/bad) shocks (with the size being 90% of the consumer's income), medium (good/bad) shocks (60% of income), small (good/bad) shocks (30% of income) and no shock (0% of income). I assume that the shocks are independent and identically distributed, drawn each period from a symmetric distribution in which larger shocks are less likely to realize. This distribution is more flexible than parametric continuous distributions such as normal or beta.

$$Y_t = Y\left(1 - \varepsilon_t\right)$$

$$\varepsilon_t \in \{-0.9, -0.6, -0.3, 0, +0.3, +0.6, +0.9\}$$

$$p_\varepsilon = \left(p_{lg}, p_{md}, p_{sm}, p_0, p_{sm}, p_{md}, p_{lg}\right),\ 0 \leq p_{lg} \leq p_{md} \leq p_{sm} \leq p_0,\ 2p_{lg}+2p_{md}+2p_{sm}+p_0 = 1$$

The consumer starts the first period with an initial wealth of W_1. I assume that W_1 has an exponential distribution with a mean of \$500, consistent with anecdotal evidence that subprime consumers live paycheck-to-paycheck and have small savings.[3] In the subsequent periods, the consumer starts with the savings that were endogenously determined in the previous period. I assume that these savings do not generate any interest as they are kept for short periods of time (two weeks) as cash, or in a checking account. For computational reasons, I assume that $W_t \in [0, 2000]$.

Ever Defaulted (D_t) is a binary variable that is equal to 1 if the person has ever defaulted before, and zero otherwise. Anecdotal evidence suggests that defaulting in the payday loan market results in future exclusion from the product, although in practice exceptions occur. This means that whenever $D_t = 1$, the consumer cannot borrow in the current or future periods ($L_{t+s} = 0\ for\ s \geq 0$). If the consumer has never defaulted before ($D_t = 0$) and starts this period with zero balance ($L_t = 0$), she can borrow at the rate $(r \times 100)\%$

[3]Although I do not present the results, using a uniform distribution between $[0, 2000]$ for initial wealth has little bearing on the results.

an amount of $L_{t+1} \in [L_{min}, L_{max}] = [100, 450]$.[4]

When the consumer starts a period with a non-zero loan balance ($L_t > 0$), she will have three possible choices:

- First, she can repay the loan. In this case, she pays $(1+r)\,L_t$ and will have no balance in the next period ($L_{t+1} = 0$). She will be able to borrow again in the future.

- Second, she can rollover the loan, and if she wants to and there is room to do so, increase the balance by $\delta_t \in \{0, [rL_t, L_{max} - L_t]\}$. In this case, she just pays the fee (rL_t) and carries the debt to the next period ($L_{t+1} = L_t + \delta_t$). Note that the model does not allow decreasing the balance when rolling over a loan, consistent with the lack of amortization in the market. If the person decides to increase the balance, the increase should be at least rL_t, to justify the cost of writing a new check and other paperwork.

- Third, she can default. In that case she incurs a disutility of u_D from the stigma attached to defaulting a loan, and the annoyance caused by the collection efforts of the lender, and all other pecuniary or non-pecuniary costs of default, except the cost of exclusion from the market. The borrower will start the next period with no balance ($L_{t+1} = 0$), and the "ever defaulted" variable switches to 1 ($D_{t+s} = 1\, for\, s \geq 1$), meaning she cannot use payday loans ever again.

Figure 2.1 displays this decision process as a flowchart.

The instantaneous utility (the utility in each period, separate from the continuation payoff) depends on the consumer's consumption in the period (c_t) and whether she defaults in that period ($D_t = 0,\ D_{t+1} = 1$):

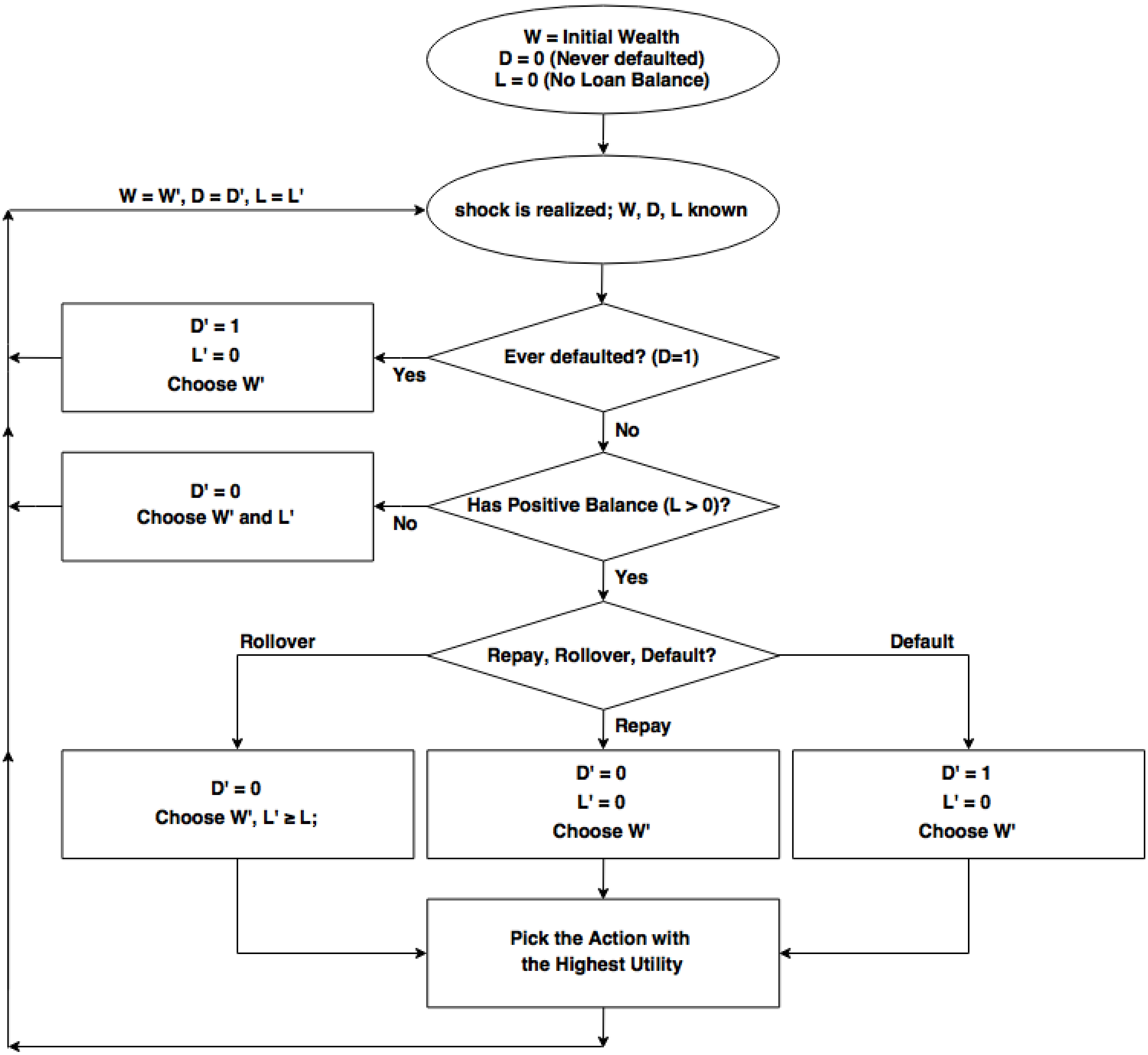
$$u(c_t, D_t, D_{t+1}) = log(c_t) - 1(D_t = 0\,\&\,D_{t+1} = 1)u_D$$

Notice that in the instantaneous utility function, U_D is incurred only once, in the period that the borrower defaults.

I assume that the consumer has naïve hyperbolic discounting. Each period, such consumer thinks to herself "Today I care mostly about today's consumption (discount the future by $\beta\delta$, $\beta < \delta$), but beginning tomorrow I will be more concerned about the future (discount the future by δ)." However, when tomorrow

[4]The upper bound is consistent with the adjustment in principal explained in section 4.

Figure 2.1: Payday Loan Consumer Decision-making Flowchart



comes, she acts the same as today (discount future by $\beta\delta$). Mathematically, this means that the continuation payoff has exponential discounting

$$\begin{aligned} V(\varepsilon, W, D, L) &= \max_{c, W', D', L'} \left\{ u(c, D, D') + \boldsymbol{\delta} \mathop{\mathrm{E}}_{\varepsilon'} V(\varepsilon', W', D', L') \right\} \\ \textit{S.t. Budget Constraints} & \end{aligned} \tag{2.1}$$

However, the actual decisions in each period are made by solving

$$\begin{aligned} (c, W', D', L') &= \operatorname*{argmax}_{c, W', D', L'} \left\{ u(c, D, D') + \boldsymbol{\beta\delta} \mathop{\mathrm{E}}_{\varepsilon'} V(\varepsilon', W', D', L') \right\} \\ \textit{S.t. Budget Constraints} & \end{aligned} \tag{2.2}$$

In this model, δ is the exponential discount factor. I set this parameter equal to $\delta = 0.99$, as is the norm in models with this setting. The parameter β captures the degree of time-inconsistency. A smaller β implies less emphasis on future well-being, and more on instant gratification. This results in borrowing, even in the absence of a consumption shock, to increase current consumption, and to procrastinate on repaying the loan, to avoid reducing current consumption. As an extreme case, when $\beta = 0$, the borrower does not solve an inter-temporal problem anymore. When $\beta = 1$, the borrower becomes neoclassical. In the next section, I find that $\beta = 0.6$ best describes the behavior of the average borrower in the data. This number is consistent with the hyperbolic discount factors assumed or estimated in the economic literature. For example, Angeletos, Laibson, Repetto, Tobacman, and Weinberg (2001) set $\beta = 0.7$ and $\delta = 0.957$ to show how self-control problems influence savings choices. Laibson (1998) also calibrates β and δ to 0.6 and 0.99, respectively, to explain undersaving.

2.3 Model Calibration

Before using the model for welfare analysis, I pick values for all parameters of the model. Above, I explained the rationale for the values I pick for the following parameters:

- Bi-weekly income: $Y = \$1100$
- Exponential (bi-weekly) discount factor: $\delta = 0.99$ (which implies an annual discount rate of about 0.8)

- Mean of initial wealth distribution $\mu(W_0) = \$500$

The free parameters include:

- Distribution of shocks $p_\varepsilon = (p_{lg}, p_{md}, p_{sm}, p_0)$
- Disutility of default u_D
- Hyperbolic discount factor β

The goal is to set the free parameters in a way that the simulated means ($\bar{y}_{i,s}$) and the empirical means ($\bar{y}_{i,e}$) are close. I pick 8 means for this purpose: Average principal, ratio of consumers with positive loan balance to all consumers[5], number of loans per sequence, and average default, each for when the fee is 15% and when it is 10%. The empirical means with 15% and 10% fees are calculated by setting the POST variable in equation ((1.1)) equal to 0 and 1 respectively, and finding the average of fitted values for Rhode Island. The goodness of fit for a set of parameter values $\boldsymbol{\theta} = (p_{lg}, p_{md}, p_{sm}, u_D, \beta)$, $\boldsymbol{\theta} \in \boldsymbol{\Theta}$, is measured in the following way:

1. Given $(p_{lg}, p_{md}, p_{sm}, u_D)$ estimate the continuation payoffs by iterating the bellman equation (2.1) until convergence is achieved. This should be done once with the fee set to 15%, and another time with the fee set to 10%. By the end of this step, there are two continuation payoff functions, one for each fee. Note that β is not required for this step, because the continuation payoff has exponential discounting.

2. Given the continuation payoff and the value of parameter β, simulate the behavior of N consumers ($N = 500$) in T periods ($T = 130$ "bi-weeks", or 5 years) using equation (2.2), separately for each fee.

3. Calculate the mean square error of the difference between the simulated and empirical means.

$$\text{MSE}(\boldsymbol{\theta}) = \frac{\sum_{i=1}^{8} \left(\frac{\bar{y}_{i,s} - \bar{y}_{i,e}}{\bar{y}_{i,e}} \right)^2}{8} \tag{2.3}$$

The goal is to find an optimal set of fee parameter values ($\boldsymbol{\theta}^*$) that minimizes equation 2.3. Since re-evaluating MSE($\boldsymbol{\theta}$) for each marginal change in a parameter requires solving two dynamic programming problems, plus the simulations,

[5]For the empirical value, "all consumers" refers to the 23,000 unique people who got a loan at some point in the sample. For the simulated value, it refers to the number of consumers used in the simulation (N=500)

it is very time consuming to employ the family of Newton's optimization methods to find $\boldsymbol{\theta^*}$. For this reason, I consider a plausible range for each parameter, and use a grid search to find the best combination. The grid for each parameter is as follows (3600 possible combinations):

$p_{lg} \in \{0.01, 0.02, ..., 0.05\}$

$p_{md} \in \{0.06, 0.07, ..., 0.15\}$

$p_{sm} \in \{max(0.10, p_{md}), ..., 0.15\}$

$u_D \in \{0.2, 0.3, 0.4, 0.5\}$

$\beta \in \{0.2, 0.4, 0.6, 0.8, 1\}$

The grid search results in the following parameter values: $\boldsymbol{\theta^*} = \left(p^*_{lg}, p^*_{md}, p^*_{sm}, u^*_D, \beta^*\right) = (0.04, 0.11, 0.14, 0.4, 0.6)$. A probability of 0.04, 0.11, and 0.14 for a large, medium, and small shocks implies that such shocks are likely to happen about once, thrice, and 4 times per year, respectively. The estimated disutility of default (0.4) means that the instantaneous effect of default on utility is approximately equivalent to that of having consumption in that period divided by 1.4.

Table 2.1 compares the simulated and the empirical means for these parameter values. The direction of change caused by lower fees is the same as the reduced form results for all variables. The biases between the variables' empirical and simulated means are also reasonably small.

I explained before how having different βs can result in different borrowing behavior. In Table 2.2, I contrast the borrowing/saving behavior of consumers with no saving or loan balance when the period begins. For this exercise, I keep all parameters constant except for β which is moved from 0.2 to 1. As can be seen in the figure, a neoclassical agent ($\beta = 1$) borrows only when she receives a big or medium bad shock, and saves in other situations. In contrast, a very time-inconsistent consumer, $\beta = 0.2$, borrows even when she receives a good consumption shock. Similarly, Table 2.3 compares the behavior of consumers with different βs, and similar otherwise, who start the period with a \$450 loan balance. Borrowers have similar default behavior, meaning that they default only when they receive a large bad shock while they are already in debt. This is a product of the "disutility of default" incorporated into the model, that makes default undesirable. Rollover/repayment behavior is very different for different βs, in the sense that neoclassical borrowers repay their loan as soon as possible, and seldom rollover a loan. The most time-inconsistent borrowers, always rollover their loans. The existence of extremely long sequences in the empirical data (1% of the sequences in the sample have more than 69 loans)

Table 2.1: Comparing Empirical and Simulated Means

Variable	With Fee	Empirical Mean	Simulated Mean	Bias = (E-S)
Principal	15%	365	338	27
Principal	10%	385	371	14
With Positive Loan Balance	15%	25%	33%	-0.08
With Positive Loan Balance	10%	28%	40%	-0.12
Default	15%	2%	2%	0.00
Default	10%	1.76%	1.5%	0.0024
Loans per Sequence	15%	4.1	3.8	0.3
Loans per Sequence	10%	5.1	4.8	0.3

The simulated means are obtained from simulations of the model with a parameter calibration that generates the smallest sum square error. The empirical means with 15% and 10% fees are calculated by setting the POST variable in equation ((1.1)) equal to 0 and 1 respectively, and finding the average of fitted values for Rhode Island. "With Positive Loan Balance" is the percentage of consumers each month who have a positive loan balance. To make the pre- and post-period sequences comparable, the number of loan in sequence is calculated for intervals of 18 months (consistent with the reduced form analysis).

supports the idea that such borrowers indeed exist.

The simulations are repeated 5 times, each time for 500 consumers in 130 periods. In each repetition, the initial wealth of consumers, and the realization of consumption shocks among consumers and periods change, while the underlying distributions remains the same. Figures 2.2, 2.3, and 2.4 display the simulated average principal, loan per sequence, and average default for when the fees are 10% and 15%. While $\beta = 0.6$ matches the empirical data the best, other βs are displayed for comparison. As can be seen, lower fees increase the principal, make the sequences longer, and decrease default, which are all consistent with the empirical results.

2.4 Welfare Analysis

Taking an *ex ante* lifetime welfare view, given the consumption path ($\{c_t\}_{t=0}^{T}$) and default path ($\{D_t\}_{t=0}^{T+1}$) for a consumer, welfare (in T periods) is measured as the (exponentially) discounted sum of instantaneous utilities at time 0:

$$\text{Welfare}(\{c_t\}_{t=0}^{T}, \{D_t\}_{t=0}^{T+1}) = \sum_{t=0}^{T} \delta^t u(c_t, D_t, D_{t+1})$$

Table 2.2: Effect of Time-inconsistency on Saving/Borrowing Behavior

Beta							
0.2	-386	-450	-450	-450	-450	-450	-450
0.4	0	-100	-221	-323	-450	-450	-450
0.6	400	200	0	-105	-259	-386	-450
0.8	741	491	235	0	-125	-307	-450
1	975	700	415	170	0	-221	-386
	-90%	-60%	-30%	0%	30%	60%	90%	Shock Size (ε)

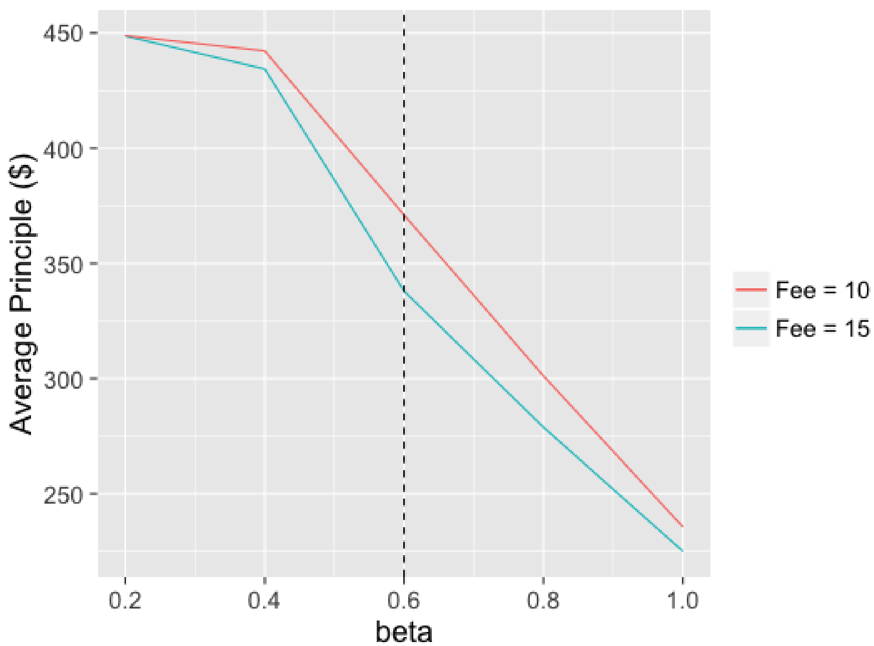
This graph shows the saving/borrowing behavior of consumers with different degrees of time-inconsistency (β) in response to different shock sizes. Note that $Y_t = Y(1-\varepsilon_t)$, therefore a negative shock size indicates an increase in income. These numbers are for a consumer with no saving and no loan balance, when the payday loan fee is 15%. Positive numbers show saving, and negative numbers show borrowing. The most time-inconsistent consumers ($\beta = 0.2$) always borrow even when they receive a good shock. The neoclassical borrowers ($\beta = 1$) borrow only when they receive large or medium bad shocks.

Table 2.3: Effect of Time-inconsistency on the Choice of Default/Rollover/Repay

Beta							
0.2	Rollover	Rollover	Rollover	Rollover	Rollover	Rollover	Default
0.4	Repay	Rollover	Rollover	Rollover	Rollover	Rollover	Default
0.6	Repay	Repay	Rollover	Rollover	Rollover	Rollover	Default
0.8	Repay	Repay	Repay	Rollover	Rollover	Default	Default
1	Repay	Repay	Repay	Repay	Rollover	Default	Default
	-90%	-60%	-30%	0%	30%	60%	90%	Shock Size (ε)

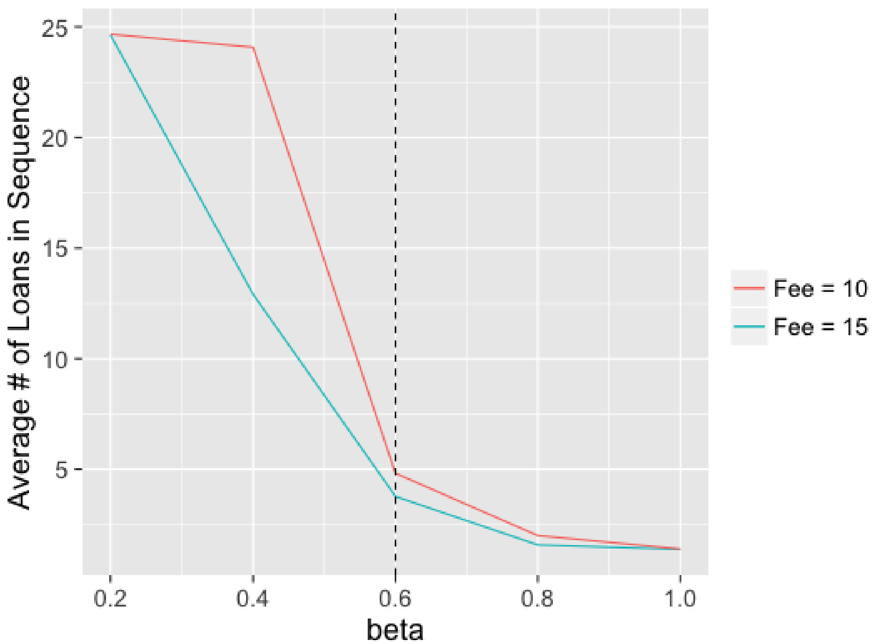
This graph shows the choice among default/rollover/repay for consumers with different degrees of time-inconsistency (β) in response to different shock sizes. Note that $Y_t = Y(1-\varepsilon_t)$, therefore a negative shock size indicates an increase in income. These choices are for a borrower with no saving and a \$450 payday loan balance, when the payday loan fee is 15%. All borrowers default when they receive a large bad shock. The most time-inconsistent borrowers ($\beta = 0.2$) always rollover their loans, even when they receive a good shock, because they want to avoid the drop in present consumption that follows repaying a loan. The neoclassical borrowers ($\beta = 1$) repay their loan as soon as they receive a good shock or no shock.

Figure 2.2: Simulation Results for Average Principal



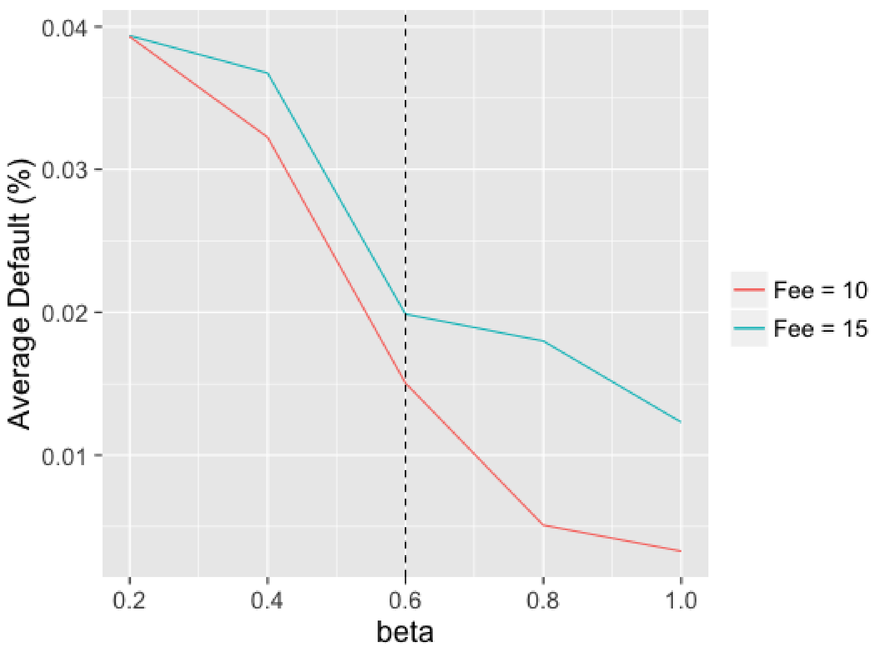
This graph compares average principal when the fee is 15% to when it is 10% for the simulations of the dynamic payday loan usage model. When the fee is lower, borrowers (regardless of the degree of time-inconsistency) borrow more money. $\beta = 0.6$ is the most compatible with the average consumer in the empirical data.

Figure 2.3: Simulation Results for Number of Loans per Sequence



This graph compares the number of loans per sequence when the fee is 15% to when it is 10% for the simulations of the dynamic payday loan usage model. When the fee is lower, the sequences become longer for time-inconsistent borrowers. For the most time-inconsistent borrowers ($\beta = 0.2$) the sequences were already so long that they could not get any longer when the fee goes down. $\beta = 0.6$ is the most compatible with the average consumer in the empirical data.

Figure 2.4: Simulation Results for Average Default



This graph compares average default when the fee is 15% to when it is 10% for the simulations of the dynamic payday loan usage model. When the fee is lower, default decreases for all types of borrowers. . $\beta = 0.6$ is the most compatible with the average consumer in the empirical data.

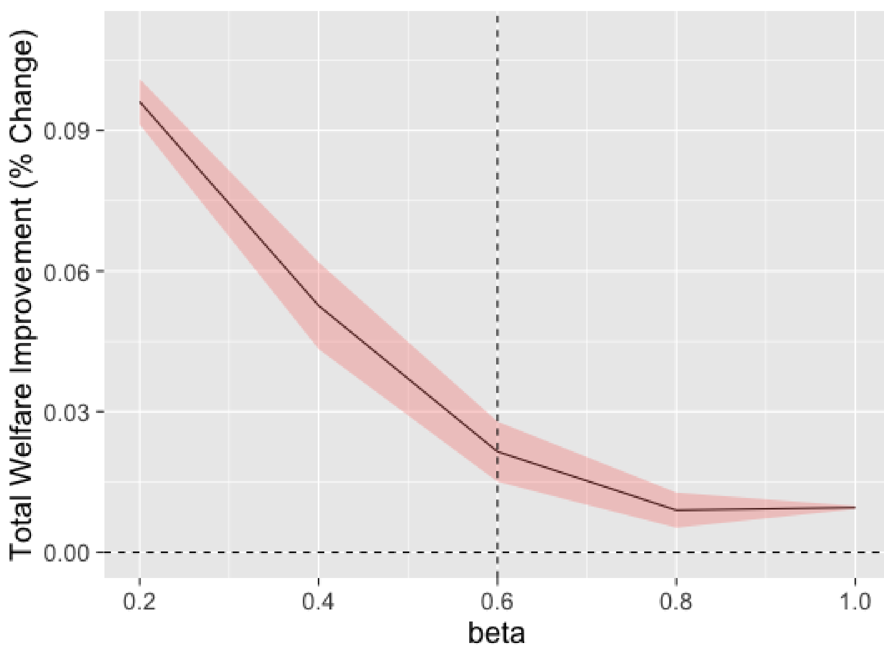
Note that there is no β in this equation. In other words, everyone's welfare is being measured by a rational consumer's criterion. This implicitly assumes irrational consumers understand that rational behavior is optimal, but are unable to commit to it.

Figure 2.5 shows the welfare improvement for decreasing the fee from 15% to 10%. The simulation shows that everyone, regardless of their β, benefits from the lower fees. The benefit for those with high β (close to neoclassical behavior) is small because they rarely use payday loans. The more time-inconsistent borrowers benefit the most from the lower fees. They show more time-inconsistent behavior when the fees go down (they borrow more amounts and rollover more often, as seen in Figures 2.2 and 2.3). On the other hand, they are paying less for each loan. The second effect seems to dominate, and they are better off in net.

I also examine the effect of removing the payday loan market. Figure 2.6 displays the welfare change caused by prohibiting payday loans compared to a base case market with a fee of 10%. The results are in line with what we would expect. The neoclassical consumers who use payday loans "rationally" would be harmed by becoming credit-constrained. Time-inconsistent borrowers, on the other hand, seem to benefit from removing the market, implying that, for them, the welfare loss from time-inconsistent behavior is larger than the welfare loss from being more credit-constrained. The average consumer (with $\beta = 0.6$) seems to fare better when the market is removed.

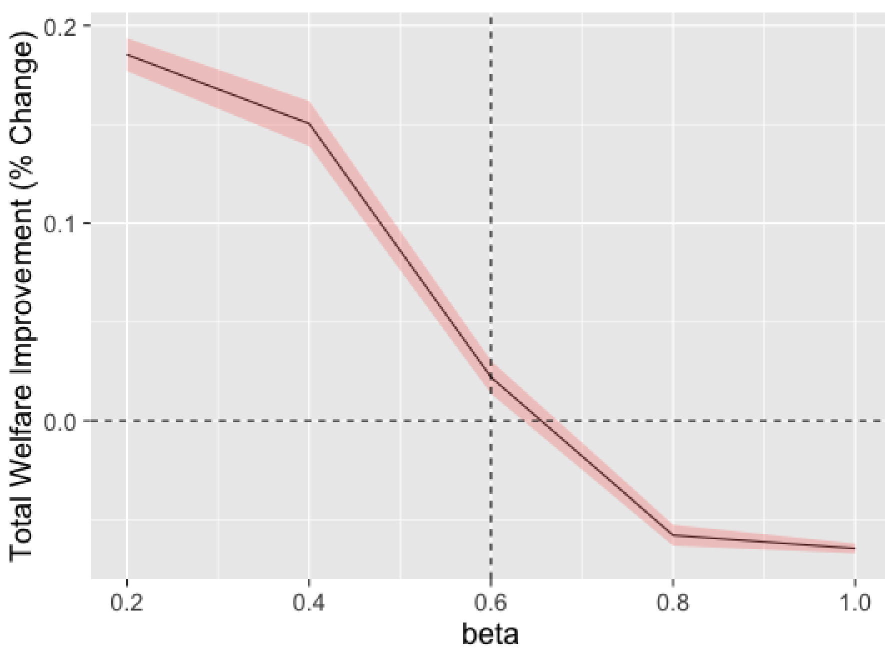
To conclude, it seems that the average (representative) borrower benefits from a lower fee cap, and even more from removing the market. But as we may reasonably believe that consumers with different degrees of time-inconsistency exist in the market, a tighter fee cap similar to the one studied in this paper would benefit all of them, whereas removing the market would harm one group (the neoclassical consumers) and benefit the others. Which policy is superior, therefore, depends on policymakers' preferences regarding the social groups they intend to protect. As in any other theoretical model, the caveat is that these results are only as reliable as the underlying assumptions of the model, especially the main one, that consumers have hyperbolic discounting.

Figure 2.5: Welfare Improvement for Lowering the Fee Cap (Simulation Result)



This graph shows the average welfare improvement caused by bringing the fee cap down from 15% to 10%, calculated from simulations of the dynamic payday loan usage model. The band represents two standard deviations above and two standard deviations below the average improvement. Consumers with different degrees of time-inconsistency benefit from the lower fees. The more time-inconsistent borrowers benefit slightly because they rarely use payday loans. The most chronic users (those with low β) benefit the most. $\beta = 0.6$ is the most compatible with the average consumer in the empirical data.

Figure 2.6: Welfare Improvement for Removing the Payday Loan Market (Simulation Result)



This graph shows the average welfare improvement, calculated from simulations of the dynamic payday loan usage model, caused by removing the payday loan market compared to a base case market with a fee of 10%. The band represents two standard deviations above and two standard deviations below the average improvement. The average borrower ($\beta = 0.6$) and the more time-inconsistent borrowers benefit from removing the market, while the more time-consistent borrowers are harmed from losing access to a source of credit.

2.5 Conclusion

One approach to measuring welfare, while taking the negative effects of payday loans into account, is to assume that the borrowers have present-bias, which leads to their borrowing more, and procrastinating more on repaying the loans, to keep their current consumption high. Lower fees would encourage this behavior and could lead to welfare decreases. I developed a model of payday loan usage in which consumers have naïve-hyperbolic discounting. I tailored the model to imitate the institutional settings of payday loans in Rhode Island, and calibrated the parameters so that the simulated means are close to the empirical ones. Simulations of this model showed that even when taking the time-inconsistent behavior into account, consumers would be better off with lower fees because the increase in time-inconsistent behavior is not large enough to dominate the utility gains from the lower cost of usage. Simulations also show that removing the market, compared to tightening the fee caps, is even more welfare improving for the average borrower (who is time-inconsistent), but would harm the time-consistent borrowers. If we accept that consumers with different degrees of time-inconsistency exist in the market, a tighter fee cap would benefit all of them (although at different levels), whereas removing the market would hurt one group (the more time-consistent consumers) and benefit the others. The preferable policy, therefore, depends on the weight that policymakers place on the well-being of the different social groups they intend to protect.

Chapter 3

Earthquake Risk Salience and Housing Prices: Evidence from California

3.1 Introduction

The purpose of this paper is to examine whether the salience of natural disasters in a housing market is affected by the occurrence of out-of-the-market natural disasters. In hedonic pricing models, the value of a house is determined by its own characteristics (such as age, square footage, and number of bedrooms), as well as those of its environment (such as proximity to good schools and air quality). Another factor in the latter category is vulnerability to natural disasters like earthquakes and hurricanes. For example, Brookshire et al. (1985) demonstrate that in California, information on earthquake hazards that were made available by a 1974 state law created a market for safe housing that previously did not exist. Each person has a perception about the likelihood of an earthquake hitting the area in which they live, own, or intend to buy. This perception is primarily based on objective information, such as seismic hazard maps published by scientific and government authorities; but it can also be subject to psychological biases.

In this paper, I investigate the existence of one form of such biases, namely, panicking after learning the news of a disastrous earthquake outside of the market, and subsequently increasing the salience (or subjective probability) of earthquakes in the market. The idea is that the news of an earthquake accentuates the potential damages and casualties such incidents can cause. It reminds individuals that the danger may be closer than it seemed, thereby making them panic and leading them to re-assess their own risks. In psychology literature, this phenomenon is referred to as "affective reactions." Slovic and Weber (2002) explain

> One of the ways in which the affective processing of a potentially dangerous situation is of value is as a signal that some action needs to be taken to reduce the diagnosed risk. The feeling of fear, dread, or uneasiness will serve as salient and potent reminder to take such action and should remain in place until such action is completed and the "impending danger flag" can be removed.

This "need to take action" can manifest itself in the housing market in the form of a higher willingness to sell and a lower willingness to buy high-risk homes. This would lead to a transfer of extra bargaining power from the sellers of high-risk homes to the buyers, resulting in lower prices for such homes. I compare home prices between low- and high-hazard zip codes in California, before and after catastrophic earthquakes that take place in other parts of the world. A significant but temporary decrease in prices of high-hazard zip codes after a distant earthquake can be taken as evidence of such bias.

California is a particularly suitable place to test this hypothesis because state laws emphasize availability and transparency of information regarding earthquake hazard. Specifically, two provisions in Alquist Priolo Act serve this purpose in the housing market:

- The law directs the California Geological Survey agency to compile detailed maps of the surface traces of known active faults. These maps include both the best known location where faults cut the surface and a buffer zone around the known trace(s);
- The law requires property owners (or their real estate agents) to formally and legally disclose that their property lies within the zones defined on those maps before selling the property.

Earthquakes with higher damages and casualties are expected to induce a larger bias for two reasons. First, they receive more extensive press coverage, making the news known to more individuals. Second, the more disastrous an event, the more profound the impact on the public's psyche. Moreover, we expect the subjective probability to return to its long-run equilibrium once the mental images of death and destruction fade into the background.

In this paper, I find that earthquakes in other parts of the world indeed affect home prices in California (measured by Zillow's Home Value Index (ZHVI) and Zillow's median listing price). According to the easiest-to-interpret specification, after a catastrophic earthquake (with more than 1000 casualties), ZHVI and median listing price fall by about 6% and 3% respectively in high-risk zip codes (with a Peak Ground Acceleration of 0.65 or greater) relative to low-risk zip codes (with a PGA of less than 0.18). To put this number into perspective, Black (1999) shows that all else equal, having an additional room adds about 3% to the value of a house. Additionally, I find that the effect on prices is transient and disappears after one month. Finally, I show that higher casualties lead to larger price decreases.

A similar paper to this is McCoy and Walsh (2014) which investigates the effect of wildfires on risk perceptions. They find that for properties located further than 5 km from a fire (but in the same county) and without a view of a wildfire burn scar, housing values in high-risk zones, relative to housing values in low-risk zones, incur a loss in the range of 6% - 9% in the year immediately following a wildfire. They also show that the price effects become statistically insignificant after two years. Another paper in this spirit is Naoi et al. (2009), that shows the price discount from locating within a quakeprone area is significantly larger soon after earthquake events (in Japan) than beforehand. These two papers look at the effect of events on areas not directly affected by the events, but still within the same county or country, while my paper looks at global events. My paper is most closely related to Boes et al. (2015) in that it studies out-of-market/non-local impacts. Boes et al. find that rents near nuclear power plants in Switzerland decreased by 2.3% after the Fukushima nuclear power incident, implying that individuals increased their subjective probability of nuclear plant incidents. My paper is unique because while Boes et al. focus on a single incident, I use all significant earthquakes that occurred around the world over a twenty year period. Furthermore, my paper allows the effect on home prices to be commensurate with the number of casualties, which gives us further insight into how salience evolves.

The rest of the paper is structured as follows. In section 2, I describe the data. In section 3, I lay out the research design. In section 4, I present and discuss the results. Section 5 concludes.

3.2 Data

I combine three datasets for this analysis:

- Seismic Hazard (Earthquake potential damages) data from United States Geological Survey (USGS), 1996
- Records of significant earthquakes from National Oceanic and Atmospheric Administration (NOAA), 1997-2016
- Monthly zip-code level home price indices from Zillow, 1997-2016

In what follows, I explain each dataset in detail.

3.2.1 Seismic Hazard Data (USGS)

This dataset contains Peak Ground Acceleration (PGA) that can happen with a probability of 10% in the next 50 years for each geographical coordinate (latitude and longitude, rounded to the closest first decimal). PGA is the maximum ground acceleration that occurs during earthquake shaking at a location. The unit of PGA in the data is g (g being the gravitational acceleration). So a PGA of 1 means ground acceleration would be equal to the gravitational acceleration. According to USGS, higher PGAs are directly linked to higher damages, with a PGA of 0.65 and above being expected to cause heavy or very heavy damage (Group, 2001).

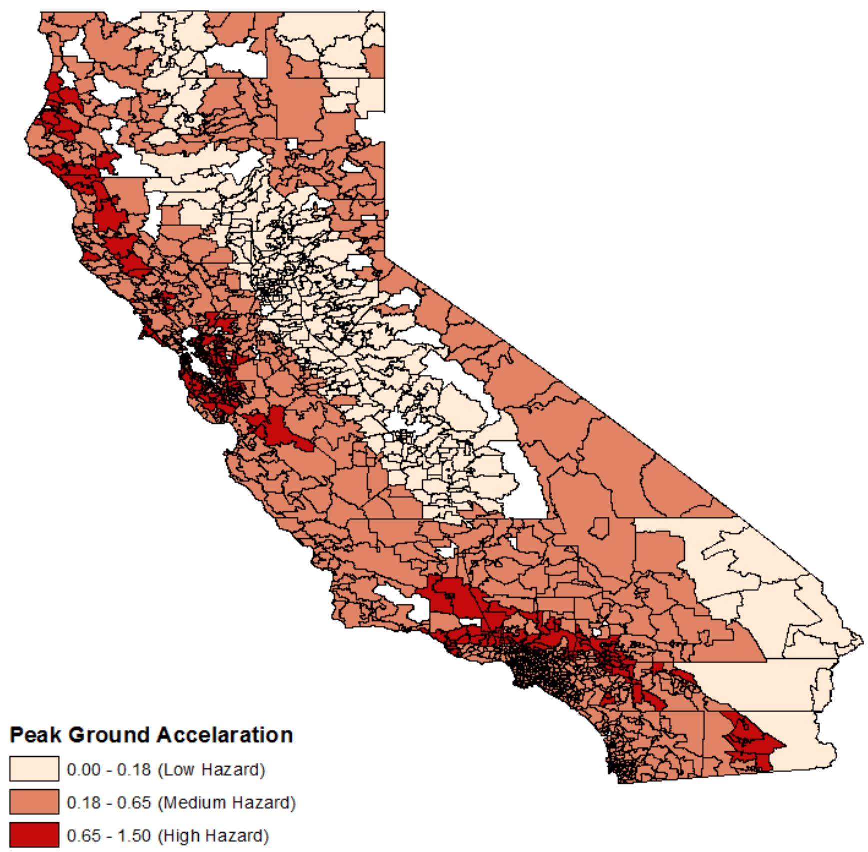
I use another dataset that includes zip code boundaries in California, and match each zip code to a PGA, based on its centroid coordinates. Figure 3.1 shows the PGA for zip codes in California, in which darker shades of red represent higher PGA, and therefore, heavier potential damages.

3.2.2 Records of Significant Earthquakes (NOAA)

According to NOAA[1], a significant earthquake meet at least one of the following criteria: approximately $1 million or more in damages, 10 or more deaths, has a magnitude of 7.5 or greater, a modified Mercalli Intensity X or greater, or the earthquake generated a tsunami. With this definition, there are 1042 significant

[1] https://www.ngdc.noaa.gov/nndc/struts/form?t=101650&s=1&d=1

Figure 3.1: PGA for California zip codes



earthquakes from the beginning of 1997 to the end of 2016 (20 years), 13 of which occurred in California. This means that at least one significant earthquake happened every month during these twenty years. I use the number of casualties as a proxy for press coverage and for the depth of an earthquake's impact on public psyche. As for earthquakes that happen in California (13 of them in the data), I control for them separately regardless of the number of casualties, because experiencing a ground shake can affect one's salience, even if no damage is incurred.

3.2.3 Home Prices (Zillow)

Zillow provides different home value indices. The most granular one, the Zillow Home Value Index (ZHVI) is available monthly at the zip code level, and goes back twenty years. To create this index, Zillow receives home sales data from counties and other municipalities. Then it uses those data in an algorithm to create an estimate (Zestimate) for the value of all homes within a zip code in a month. ZHVI is the median value of zestimates in each zip code. Because this index is constructed taking into account all homes for which Zillow has data rather than only those that are sold, the changes in values are less sensitive to selective home sales (Sanders, 2014).

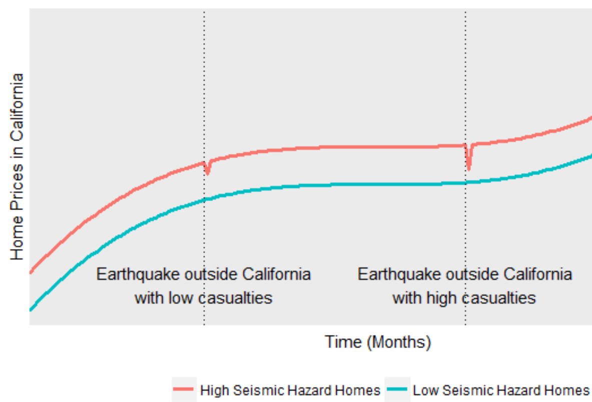
In addition to ZHVI, I use Median List Price per sq. ft. which is equal to the raw median of home prices (per square foot) listed on Zillow for sale. This variable is available only for 2010 on.

While home price data is monthly, earthquakes can happen on any day within the month. Therefore, if an earthquake occurred in the second half of the month ($day > 15$) I assign it to the next month, before merging the price data and earthquake data.

3.3 Research Design

To test the hypothesis that earthquake salience increases in a market in response to out-of-the-market earthquakes, I examine whether home prices fall in earthquake-prone zip codes after a significant earthquake happens in any other part of the world. To capture this effect, I use a difference-in-difference framework, which basically compares home values between high- and low-hazard zip codes, and between the aftermath of an earthquake and other months (no earthquake or small casualties). Figure 3.2 illustrates this identification strategy.

Figure 3.2: Identification Strategy illustrated (Does not display actual data.)



The estimating equation is:

$$P_{zt} = \rho + \beta \cdot PGA_z \cdot GLOBALCasualties_t + \sum_k b_k \cdot PGA_z \cdot GLOBALCasualties_{t-k} +$$
$$\alpha \cdot PGA_z \cdot CACasualties_t + \sum_k a_k \cdot PGA_z \cdot CACasualties_{t-k} + \gamma_z + \lambda_t + \varepsilon_{zt} \tag{3.1}$$

The outcome of interest is home price in zip code z at time (month) t, as measured by ZHVI, or listing price per sq ft. The coefficient of interest is β which measures the differential effect of a non-California quake between high-hazard and low-hazard zip codes. Zip Code fixed effects (γ_z) capture all time-invariant characteristics of each zip code, while time fixed effects (λ_t) control for state-wide shocks in each period. Furthermore, I separately control for earthquakes happening in California, to avoid confounding the effect of global earthquakes.

The model includes lags to test whether the price effects last over time. However, we do not expect the effect to be long lasting. Lobb et al. (2012) show that after the Haiti earthquake in 2012, related Twitter posts, press releases, newspaper stories, and charitable donations peaked one week after the event, and almost disappeared less than a month after the earthquake. As individuals forget about the event within a month, the effects on salience are also likely to decay within the same time frame. Furthermore, as a robustness check, I estimate another variant of equation 3.1 that includes leads along with the lags.

This practice is to insure the results are indeed driven by the earthquakes, not by anticipation thereof which is impossible.

I will estimate variants of equation 3.1 in which I use a categorical variable (low, medium, and high hazard) instead of a continuous measure of PGA, because it is conceivable that most individuals do not know the exact measure of seismic hazard in their area, but have a rough idea about its level. I also use a dummy variable for the extent of casualties (high casualty, as defined by having a death count of above 1000 and low casualty otherwise). This practice is mainly to achieve coefficients that are easier to interpret.

3.4 Results

Tables 3.1 and 3.2 show the results for estimating equation 3.1 with ZHVI and median listing price as the outcome of interest, respectively. Specification (I) includes no lags or leads. Specification (II) includes two lags, which turn out to be insignificant at the 5% level. (I also tried higher lags with similar results, not reported in the paper.) In specification (III), I also include leads as a falsification test. In all specifications, and for both outcomes, the same-period effect is significant at the 1% level. This implies that earthquakes outside California can asymmetrically affect home prices in California, based on whether the home is known to be in a high hazard area or not. The results also show that the higher an earthquake's casualties, the larger the asymmetry.

It is worth mentioning that Zillow's algorithm for creating ZHVI may smooth out the sharp movements of prices, and hence make the coefficients in table 3.1 an underestimation of the actual effects. For this reason, the results for median list price (which is a raw measure) may provide a more accurate measure of the price effects.

In table 3.3, I transform continuous measures into categorical ones, to make the results easier to interpret. I control for California earthquakes using a dummy variable (1 if an earthquake happened in California in a given period, and 0 otherwise), instead of the number of casualties (which are always less than 3 for California earthquakes in the data). I cannot do the same for non-California earthquakes because they occur so often almost every period would be flagged as having an earthquake. Therefore, I set a threshold of 1000 casualties for a non-California earthquake to count as impactful. There are 20 of such earthquakes between 1997 and 2016. Moreover, instead of using PGA as a continuous measure of seismic hazard, I define a low-hazard zip code as having a PGA of 0.18 or lower, a medium hazard zip code as having a PGA between 0.18 and 0.65, and a high hazard zip code as having a PGA of more than 0.65 (in accordance to Group (2001)). The results show that a high-casualty earthquake can cause ZHVI and median asking price to drop by about 5% and 2% in medium-risk zip codes (relative to low-risk zip codes), and by about 6% and 3% in high-risk zip codes (relative to low-risk zip codes). These effects are approximately equivalent to the effect of having 1.5 additional rooms in a house (all else unchanged).

In all of these regressions, the lags are statistically insignificant at the 5% level, implying that the adjustments in subjective probability are temporary and do not extend beyond one month after the earthquake. In addition, all coefficients on leads turn out statistically insignificant at the 5% level in all regressions, providing evidence that the results are not spurious.

The earthquakes that happened in California could have affected home prices directly by causing damage to buildings and infrastructure. Since in this paper I am solely interested in the effect of salience, I exclude zip codes within a 10-mile radius of the center of the earthquakes from the sample. The removed zip codes are marked in figure 3.3. Table 3.4 compares the results for estimating equation 1 with the unrestricted sample (all zip codes) and the restricted sample (zip codes not directly affected by earthquakes). Consistent with what we expect, the effect of California earthquakes on prices shrinks slightly when using the restricted sample.

3.5 Conclusion

Based on hedonic pricing models, we expect the price of a house to reflect its environmental characteristics, including vulnerability to natural disasters. In this paper, I examine whether earthquake risk salience increases in an area in response to the news of earthquakes in other parts of the world. The change in salience can also be thought of as an adjustment in individuals' subjective probability of an earthquake occurring in their area. To test this hypothesis, I use a difference-in-difference framework to see if earthquakes happening in other parts of world affect home prices in quake-prone zip codes in California. I show that a catastrophic out-of-California earthquake decreases prices (as measured by the Zillow home price index, and median listing price per sq ft) in earthquake-

Table 3.1: Regression Results for ZHVI

Dependent Variable	*log(ZHVI)*		
Specification	(I)	(II)	(III)
PGA * Non-CA Casualties (in 1000s)	-0.000126 *** (0.000046)	-0.000127 *** (0.000046)	-0.000125 *** (0.000046)
Lag 1 Month		-0.000077 * (0.000046)	-0.000078 * (0.000047)
Lag 2 Months		-0.000082 * (0.000046)	-0.000074 (0.000046)
Lead 1 Month			-0.000060 (0.000046)
Lead 2 Months			0.000056 (0.000046)
PGA * CA Casualties (individuals)	-0.010337 (0.006966)	-0.009690 (0.006993)	-0.0102774 (0.007000)
Lag 1 Month		0.009689 (0.006984)	0.009856 (0.007000)
Lag 2 Months		0.011239 (0.006976)	0.010193 (0.006996)
Lead 1 Month			-0.006465 (0.006984)
Lead 2 Months			-0.001808 (0.006995)
Zip Code F.E.	Y	Y	Y
Time F.E.	Y	Y	Y
R squared	0.97	0.97	0.97
Number of Observations	267,821	265,596	263,355

Significance levels: *** (1%), ** (5%), * (10%)

Table 3.2: Regression Results for Median Listing Price

Dependent Variable	*log(Median List Price per sqft)*		
Specification	(I)	(II)	(III)
PGA * Non-CA Casualties (in 1000s)	-0.000437 ***	-0.000448 ***	-0.000402 ***
	(0.000056)	(0.000056)	(0.000057)
Lag 1 Month		0.000023	0.000034
		(0.000036)	(0.000036)
Lag 2 Months		-0.000020	-0.000010
		(0.000036)	(0.000036)
Lead 1 Month			0.000058 *
			(0.000035)
Lead 2 Months			-0.000013
			(0.000036)
PGA * CA Casualties (individuals)	-0.004089	-0.004008	-0.005092
	(0.008685)	(0.008788)	(0.008941)
Lag 1 Month		-0.004579	-0.003533
		(0.011387)	(0.011484)
Lag 2 Months		0.004909	0.004314
		(0.010905)	(0.011127)
Lead 1 Month			-0.015171
			(0.011159)
Lead 2 Months			0.009439
			(0.011282)
Zip Code F.E.	Y	Y	Y
Time F.E.	Y	Y	Y
R squared	0.99	0.99	0.99
Number of Observations	45,290	44,209	43,171

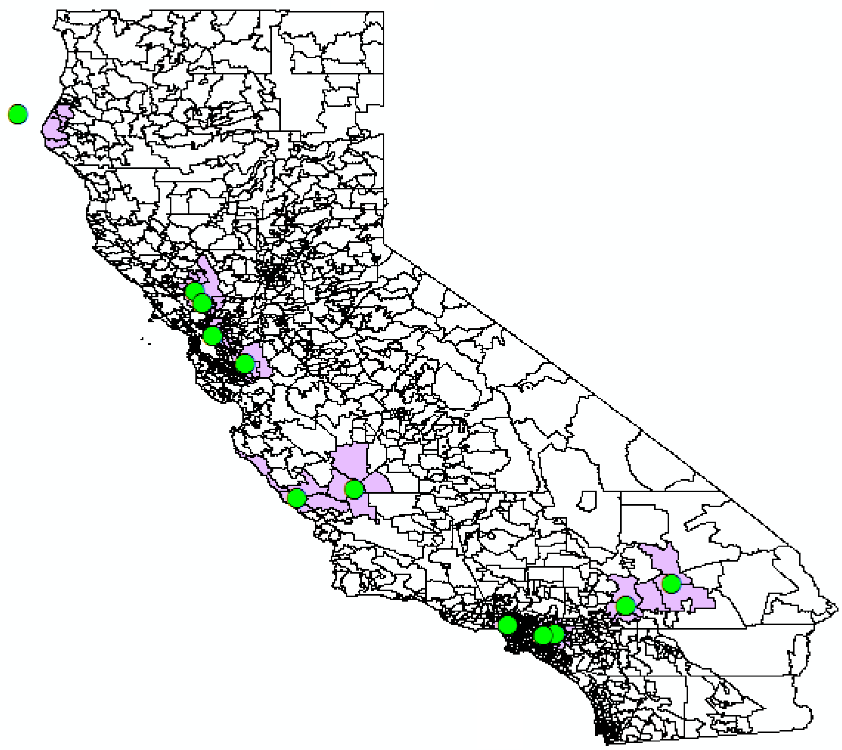
Significance levels: *** (1%), ** (5%), * (10%)

Table 3.3: Regression results with categorized PGA and casualties

Dependent Variable	*log(ZHVI)*	*log(List Price per sqft)*
Specification	(III)	(III)
(.18 < PGA < .65) * (non-CA Casualties > 1000)	-0.053 ***	-0.020 ***
	(0.002)	(0.004)
Lag 1 Month	-0.002	0.002
	(0.002)	(0.004)
Lag 2 Months	-0.003	0.005
	(0.002)	(0.004)
Lead 1 Month	0.001	0.006
	(0.002)	(0.004)
Lead 2 Months	-0.002	0.001
	(0.002)	(0.004)
(PGA > .65) * (non-CA Casualties > 1000)	-0.057 ***	-0.030 ***
	(0.003)	(0.005)
Lag 1 Month	-0.004 *	0.003
	(0.003)	(0.005)
Lag 2 Months	-0.004	0.007
	(0.003)	(0.005)
Lead 1 Month	-0.003	0.003
	(0.003)	(0.005)
Lead 2 Months	-0.001	0.000
	(0.003)	(0.005)
(.18 < PGA < .65) * (CA earthquake)	-0.011 ***	-0.008 **
	(0.003)	(0.004)
Lag 1 Month	-0.001	0.002
	(0.003)	(0.004)
Lag 2 Months	0.004	-0.001
	(0.003)	(0.004)
Lead 1 Month	0.001	0.002
	(0.003)	(0.004)
Lead 2 Months	0.001	0.007
	(0.003)	(0.004)
(PGA > .65) * (CA earthquake)	-0.014 ***	-0.016 ***
	(0.003)	(0.005)
Lag 1 Month	0.002	0.005
	(0.003)	(0.005)
Lag 2 Months	0.001	-0.004
	(0.003)	(0.005)
Lead 1 Month	-0.000	0.003
	(0.003)	(0.005)
Lead 2 Months	0.002	0.003
	(0.003)	(0.005)
Zip Code F.E.	Y	Y
Time F.E.	Y	Y
R squared	0.97	0.99
Number of Observations	263,355	43,171

Significance levels: *** (1%), ** (5%), * (10%)

Figure 3.3: Earthquakes in California, 1997-2016



Each dot represents the center of an earthquake that occurred in California, 1997-2016. The shaded areas are zip codes within a 10 mile radius from the center of the earthquake.

Table 3.4: Regression results for zip codes not directly affected by earthquakes

Dependent Variable	*log(ZHVI)*		*log(Median List Price per sqft)*	
Sample	Unrestricted	Restricted	Unrestricted	Restricted
Specification	(III)	(III)	(III)	(III)
PGA * Non-CA Casualties (in 1000s)	-0.000125 ***	-0.0001395 ***	-0.000402 ***	-0.000354 ***
	(0.000046)	(0.000050)	(0.000057)	(0.000061)
Lag 1 Month	-0.000078 *	-0.000083 *	0.000034	0.000029
	(0.000047)	(0.000050)	(0.000036)	(0.000038)
Lag 2 Months	-0.000074	-0.000075	-0.000010	-0.000014
	(0.000046)	(0.000050)	(0.000036)	(0.000040)
Lead 1 Month	-0.000060	-0.000048	0.000058 *	0.000054
	(0.000046)	(0.000050)	(0.000035)	(0.000037)
Lead 2 Months	0.000056	0.000048	-0.000013	0.000020
	(0.000046)	(0.000050)	(0.000036)	(0.000039)
PGA * CA Casualties (individuals)	-0.0102774	-0.009353	-0.005092	-0.002715
	(0.007000)	(0.007503)	(0.008941)	(0.009546)
Lag 1 Month	0.009856	0.009889	-0.003533	-0.001367
	(0.007000)	(0.007503)	(0.011484)	(0.012384)
Lag 2 Months	0.010193	0.008389	0.004314	0.002115
	(0.006996)	(0.007513)	(0.011127)	(0.011885)
Lead 1 Month	-0.006465	-0.006780	-0.015171	-0.013559
	(0.006984)	(0.007493)	(0.011159)	(0.011926)
Lead 2 Months	-0.001808	0.001267	0.009439	0.008910
	(0.006995)	(0.007512)	(0.011282)	(0.011856)
Zip Code F.E.	Y	Y	Y	Y
Time F.E.	Y	Y	Y	Y
R squared	0.97	0.97	0.99	0.99
Number of Observations	263,355	212,048	43,171	34,304

Significance levels: *** (1%), ** (5%), * (10%)

prone zip codes by about 6%, relative to the least quake-prone zip codes. The effect decays after one month. I also show that the higher the casualties of an earthquake, the larger the effect on prices.

In psychology, the change in salience in response to events that do not directly affect a person are called affective reaction. Affective reaction involves taking actions to avoid the negative impacts of a possible undesirable event. In the housing market, this translates into trying to sell a vulnerable house or to avoid buying such a house. Therefore, we would expect a drop in the prices of homes that are located in high-hazard areas. The analysis in this paper adds to the existing evidence supporting the existence of this phenomenon. The observation that the price effect decays after a month is also interesting, and could suggest that the adjustment in salience is not "rational." In this sense, this paper captures the market-level manifestation of a psychological bias overruling rational decision-making. On the other hand, one can think of a scenario in which someone owning a vulnerable building in a high-risk area has been procrastinating on selling the house but does so after feeling panicked by a distant earthquake. In this case, the reaction is rational and corrects a behavioral bias.

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Vita

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